COMBINED INTEGRATION OF WIND POWER AND ELECTRIC VEHICLES INTO SMART GRIDS

BY

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This thesis, written by **AHMED M. MAHMOUD ABD EL-MOATY** under the direction of his thesis adviser and approved by his thesis committee, has been presented to and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN ELECTRICAL ENGINEERING**.

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To the soul of my father, the soul of my departed wife, and my family

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LIST OF ACRONYMS

ARIMA	Autoregressive Integrated Moving Average
CVaR	Conditional Value at Risk
DA	Day-Ahead
DAP	Day-Ahead Pricing
DSM	Demand-Side Management
DLC	Direct load Control
ESS	Energy Storage system
EVs	Electric Vehicles
GT	Game Theory
IBR	Iterative Best Response
ISO	Independent System Operator
KKT	Karush Kuhn Tucker
KW	Kilowatt
LSE	Load Service Entity
MW	Megawatt
MGs	Micro-Grids
MILP	Mixed-Integer Linear Program

NE	Nash Equilibrium
RT	Real-Time
RTP	Real-Time Pricing
RES	Renewable Energy Sources
RO	Robust Optimization
SCUC	Security Constrained Unit Commitment
SO	System Operator
STATCOMs	Static Synchronous Compensator's
SVCs	Static Var Compensator's
TOU	Time of Use
UC	Unit Commitment
V1G	Unidirectional Vehicle-to-Grid
V2G	Vehicle-to-Grid
VPP	Virtual Power Plant
VPPO	Virtual Power Plant Operator
WBG	Wind Balancing Game
WPP	Wind Power Producer
WWEA	World Wind Energy Association

LIST OF ABBREVIATIONS

c	Index for EV.
e	Index for segments.
s	Index for scenarios.
t	Index for time periods
g	Index for thermal generators.
d	Index for wind units.
N_T	Number of time periods.
N_G	Number of thermal generator units.
N_D	Number of wind plants.
N_S	Number of scenarios.
N_E	Number of segments.
N_C	Number of EVs.
MP_c	Maximum charging power for EV c.
SOC_{I_c}	Initial state of charge of EV c in KWh.
MC_c	Maximum capacity of charge for EV c in KWh.
$Av_{c,t}$	The availability of EV c for charging at time t.
L_t	Scheduled demand at time t in MW.

R	Utility rate charged for the customers \$/MWh.
ρ	Incentive for the EV owners.
I_g^0	Initial state of thermal unit g.
$I_{g,t}$	State of thermal unit g at time t, $0 = \text{Off}$, $1 = \text{On}$.
$P_g^{\max}, P_g^{\min}$	Max/min power generation of thermal unit g,in MW.
$BrkPt_{e,g}$	Break point of a segment e for thermal unit g for the heat rate curve.
$Slpoe_{e,g}$	Slope of a segment e for thermal unit g for the heat rate curve.
K_g	Offset of thermal unit g for the heat rate curve.
FC_g	Fuel cost of thermal unit g in \$.
a, b, c	Parameters of thermal heat rate curve.
RU_g, RD_g	Ramp up/down rate of thermal unit g ,in MW/hour.
$InitUP_g$	Initial minimum up-time for thermal unit g.
$MinUP_g$	Minimum up-time for thermal unit g.
R	Percentage of regulation revenue of the Aggregator.
C_g	Energy generation cost for thermal unit g in \$.
λ_t	Day-ahead energy price for EV fleet c at time t in \$/MWh.
$PD_{c,t}$	Awarded energy bid for EV c at time t in KWh.
$AP_{c,t}^{max}$	Maximum scheduled increase power for EV c at time t in KW.
$AP_{c,t}^{min}$	Maximum scheduled reduction power for EV c at time t in KW.
$POP_{c,t}$	Preferred operating point for EV c at time t in KW.
$W_{d,t}^{bid}$	The optimal bidding of wind unit d at time t in MW.
$P_{g,t}^{bid}$	The optimal bidding of thermal unit g at time t in MW.

$P_{g,t}^{RT}$	The real time realized power of thermal unit g at time t in MW.
$\delta_{g,e,t}$	Output of thermal unit g at time t corresponding to segment e in MW.
Imb_t^{up}	Over-generation power from the scheduled at time t in MW.
Imb_t^{dn}	Under-generation power from the scheduled at time t in MW.
$SU_{g,t}$	Startup cost of thermal unit g at time t in \$.
W_d^{max}	Rated output of wind unit d in MW.
$W_{d,t}^{RT}$	Realized output of wind unit d at time t in MW.
L_t^{RT}	Realized demand at time t in MW.
ΔP_t	Deviation of the dispatched generation between the day-ahead (scheduled) and real-time (realized) outputs.
r^o/r^u	Over/under generation penalties as imbalance multipliers of the energy price.
$T\_Dep(x)$	Time of the x^{th} EV departure.
SOC_c^{reduc}	Reduction in SOC of the c^{th} EVs' battery as a result of driving.
γ^+	Binary variables its value is 1 if the uncertain parameter at the upper bound of its set.
γ^-	Binary variables its value is 1 if the uncertain parameter at the lower bound of its set.
$\theta_w, \theta_\lambda, \theta_L$	Parameters of the uncertainty set size for wind, energy price, demand respectively.
Ω	Dummy variable.

THESIS ABSTRACT

NAME:	Ahmed M. Mahmoud Abd El-Moaty
TITLE OF STUDY:	Combined Integration of Wind Power and Electric Vehicles into Smart Grids
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Driven by the global warming, loss in green land, thermal expansion, and increase in the greenhouse gases emission, two directions have been developed to overcome these problems. Firstly, incorporating renewable energy sources (RES) such as wind power into the current power grid, and secondly, finding the most proper alternatives to the current grid components which aim to reduce these effects, such as replacing the conventional transportation sector by Electric Vehicles (EVs). With the increase of the market share of both wind power and EVs, the need for a suitable frameworks from both economical and operational views has become crucial. In this thesis, we aim to study and design such required frameworks for wind power generation companies combined with the aggregator of EVs.

One of the challenges facing the wind generation companies, such as the EVs aggregators, is the uncertainty about the available power and the energy prices. Clearly, this variability will affect the bids of the aggregators into the energy market. Despite the expanded dependence on centralized scheme for scheduling of the EV charging, the burden of computational load can grow dramatically high as the number of involved vehicles increases. In the first part of this thesis, a decentralized game theoretic approach for scheduling the EVs charging to balance the wind generation with the load is proposed. Analytically, Nash Equilibrium is proven to exist and to be unique. Moreover, a closed form solution is found. Extensive simulations for a case study of the Saudi Arabian EVs owners' behavior are conducted to validate the proposed model.

In the second part of this thesis, a market framework for virtual power plant operator (VPPO) which acts as EVs aggregator and owns wind and thermal generators is addressed. The aggregator aims to maximize his profit which he gains from bidding energy amounts in the day-ahead (DA) market. The optimal bidding strategy combined with controlling the Vehicle-to-grid (V2G) assets under the uncertainty of the wind output, energy prices, imbalance prices, and demand is addressed. The uncertainties were modeled using robust optimization (RO) under the worst case scenario of the uncertain parameters. A case study and simulations are carried out to reflect the effectiveness of the proposed model. The robust model is compared to the deterministic model, the results show that the robust model, under uncertainties, gives profits which are relatively close to the deterministic model.

ملخص الرسالة

الاسم الكامل: احمد محمد محمود عبد المعطي

عنوان الرسالة: الادماج الثنائي لطاقة الرياح والسيارات الكهربائية في الشبكات الكهربائية الذكية

التخصص: الهندسة الكهربائية

تاريخ الدرجة العلمية: مايو ٢٠١٧

انطلاقا من ظاهرة الاحتباس الحراري ، النقص في المساحات الخضراء ، التمدد الحراري ، والزيادة في انبعاث الغازات المسببة للاحتباس الحراري، تم تطوير اتجاهين بحثيين للتغلب على هذه المشاكل. الأول، هو العمل على زيادة دمج مصادر الطاقة المتجددة مثل طاقة الرياح في شبكات الطاقة الحالية. الثاني ، يعتمد على ايجاد بدائل مناسبة لمكونات الشبكة الكهربائية الحالية والتي تساعد في الخفض من تأثير هذه المشاكل مثل استبدال قطاع النقل الحالي بالسيارات الكهربائية. نظرا للزيادة المتسارعة في ادماج طاقة الرياح والسيارات الكهربائية جنبا إلى جنب في الشبكة الكهربائية الحالية فإن الحاجة الى الأطر المناسبة والتي تحاكي وجهات النظر الفنية والسوقية تعد ذات أهمية قصوى. في هذه الأطروحة، نهدف إلى دارسة وتصميم الأطر اللازمة لشركات انتاج طاقة الرياح جنبا إلى جنب مع مجمعي السيارات الكهربائية.

يعتبر عدم اليقين من كمية الطاقة المتاحة وأيضا أسعار الكهرباء واحدا من أكثر التحديات التي تواجه منتجي طاقة الرياح بالمثل مجمعي السيارات الكهربائية. بلا شك ،إن التغير في هذين العاملين سوف يؤثر على العروض التي يتقدم بها منتجو الطاقة ومجمعو السيارات في اسواق الطاقة الكهربائية. بالرغم من الاعتماد المتزايد على التحكم المركزي في جدولة عملية شحن السيارات الكهربائية، فإن مشكلة زيادة العمليات الحسابية المطلوبة تتناسب طرديا مع زيادة عدد السيارات الكهربائية الموجودة. في الجزء الأول من هذه الأطروحة، قمنا باقتراح نظام تحكم لامركزي يعتمد على نظام لعبة نظري لمجمعي السيارات الكهربائية لضمان عملية الموازنة بين الانتاج الوارد من الرياح مع الحمل. تم اثبات وجود حالة الاتزان (اتزان ناش) وكذلك كونه منفردا رياضيا. علاوة إلى ذلك، تم ايجاد حل نهائي لحالة الاتزان. تم عمل حالات محاكاة لدراسة حالة سلوك قائدي السيارات السعوديين لاثبات مدى كفاءة النموذج المقترح.

في الجزء الثاني من هذه الأطروحة، قمنا باقتراح نموذج لمشغل شبكة كهربائية صغيرة والذي يفترض أنه مجمع سيارات كهربائية بالاضافة إلى وجود مولدات طاقة رياح وكذلك مولدات حرارية. يهدف مجمع السيارات إلى تعظيم الربح العائد من عرض بيع الطاقة الكهربائية المنتجة في سوق الطاقة الكهربائية اليومي. تم عرض طريقة المزايدة الأفضل لشبكة الانتاج مع التحكم في عملية شحن السيارات الكهربائية في وجود عدم اليقين من الطاقة المنتجة من مولدات الرياح، أسعار الطاقة ، أسعار التقويم، وكذلك الأحمال. قمنا باقتراح نمذجة عدم اليقين عن طريق التهيئة المتينة بافتراض اسوأ الحالات حدوثا للعوامل غير المتيقن منها. تم عمل دراسة حالة ونظام محاكاة لاثبات فعالية النموذج المقترح. تم مقارنة النموذج المقترج بنظام التهيئة المتينة مع النظام المحدد ، أظهرت النتائج ان نظام التهيئة المتينة والذي يأخذ في اعتباره أسوأ الحالات حدوثا للمعاملات غير المتيقن منها قد حقق أرباحا لمجمع السيارات تقارب تلك التي يمكن أن يتم اكتسابها من النظام المحدد بدون اعتبارات عدم اليقين.

CHAPTER 1

INTRODUCTION

1.1 Background

The installed capacity of renewable energy sources (RES) is expanding quickly all around the globe due to the arising complaints about the greenhouse gas effects and the incremental rise in fossil fuel prices. The world wind energy association (WWEA) [2], declared that the current total installed wind capacity reached 393 GW. The global wind power installed can now supply 4% of the worldwide electricity demand. The wind energy is expected to represent 35% of the U.S. electricity by 2050 according to [1] as shown in Figure 1.1. At the same time, while working on the generation side the work continues on the demand side. The transportation sector is one of the most energy demanding sectors and the one most dependent on fossil fuels. More than one-quarter of the energy consumption in the U.S. is used for transportation [3]. As a result, this sector encountering a rush of electrification to achieve the energy security and environmental sustain-

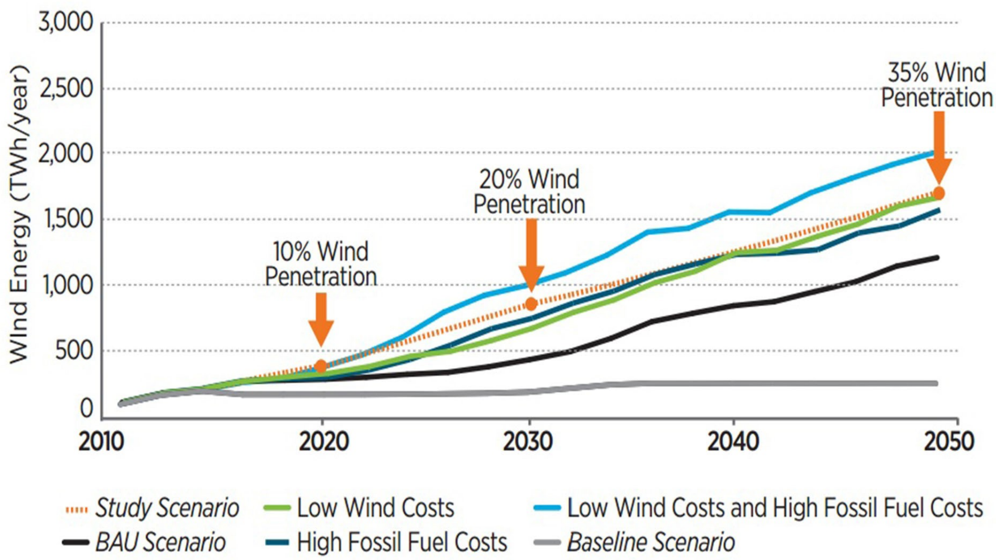

Figure 1.1: Wind Vision Study Scenario relative to BAU (Business As Usual) for USA [1].

ability. Transforming from conventional to electric vehicles (EVs) is expected to greatly enhance the energy efficiency of transportation and reduce the emission impact per vehicle tremendously.

However, integrating the RES into the power grid is companioned with extra burdens. As a result, solutions have been proposed, such as provision of Vehicle-to-grid (V2G) services. The concept of V2G is based on the fact that the EVs can be used as energy storage unit which can help the grid and can benefit both grid and EV owner, not just a load. These services can boost the adoption rate of the EVs into the grid while potentially alleviate the adverse impacts of EVs on the grid.

1.1.1 Electricity Markets

The electric power industry has moved from a regulated operational structure controlled by a single entity, usually the government, to a competitive one in many countries. Recently, the electricity industry has experienced numerous reformulation activities, including increasing the number of market participants and the establishment of market operators, and aggregators. As an example in the U.S. about two-thirds of the total load is operated in the electricity markets.

Based on the type of production to be traded, the electricity markets can be categorized into the energy market, ancillary services market, balancing market

- **Energy market**

  Energy is bought and sold in the energy market through a two-settlement process: day-ahead market and real-time market (also known as the balancing market. The day-ahead market clears energy transactions each hour of the next operating day while real-time market transactions are performed just minutes before actual power deliveries. Energy is bought and sold in the real-time market at real-time spot prices to make up imbalances when system conditions change from the day-ahead market. In some European countries, the energy market also includes an adjustment market which is similar to the day-ahead market but is cleared closer to power delivery.

- **Balancing market**

  The balancing market is when the traders have corresponded to the actual power flows. It may happen that there a certain amount of the power which is sold in the day-ahead market but may not be exactly delivered in the real-time. Tow types of imbalances can be faced by the generation companies. The positive imbalance occurs when the actual power is greater than the scheduled and the negative imbalance occurs when the actual power is lower than the scheduled power. All the involved parties are required to submit their schedules to the ISO which reflects their generation or consumption. The schedules can be modified before the real time by a certain time i.e., 1-2 hours in some markets.

- **Ancillary services market**

  In addition to the energy market, the ancillary services market ensures the reliability of the power system. Various types of ancillary services exist in the market today, such as regulation, contingency, and reserves. Other ancillary services, such as voltage control and black start services, do not typically have auction-based markets.

The participants in an energy market can be seen as a hierarchical tree with three nodes:

- **Producers**

  The generation companies who supply energy or services. Their goal is to maximize their total profits by submitting offers in the electricity market.

- **Retailers (Aggregators)**

  They usually purchase energy or services from the energy market and sell them back to the consumers who do not participate directly in the energy market due to their small capacities, i.e., EVs' owners.

- **Consumers**

  They are end-users who buy energy or services from the electricity market through the retailer or the aggregator. A consumer, e.g., EV owner can submit consumption bids to the aggregator with the goal of minimizing the cost of purchasing energy or services.

With the consequent increasing in the number of the participants in the energy market, there was a need for rules and regulations to control the selling and purchasing process, and to guarantee the secure transaction. Independent System Operator (ISO) is a neutral entity who takes these responsibilities. ISO usually used to control the transmission tariffs, coordinate the planning and maintenance schedules, play a vital role in forecasting the energy prices and demand, running the market clearing operation.

1.1.2 Wind Power

Today, around 23% of the wind power capacity in the U.S. is sold either through short-term contracts or directly into the electricity market. This percentage is expected to increase further according to [3]. To wind power producers, the uncertain characteristics of wind resources are a major obstacle to their participation in the electricity market. Compared with conventional power producers, wind power producers have negligible fuel costs and are exposed to high risks in the electricity market. The uncertainty coming from wind power production, coupled with the stochastic nature of market prices, results in uncertain profits for wind power producers.

1.1.3 Electric Vehicles and V2G Overview

The concept of Vehicle-to-grid was first introduced in [4]. On the contrary of what was previously assumed in [5], the authors in [4] suggested that the EVs are not just a load. They assumed that the EVs can be treated as energy storage units as well which can help in supporting the electrical grid and will be beneficial for the grid and EV owners. This concept was expanded further in [6]. Two charging approaches were suggested for this concept in [7]. The first one was unidirectional V2G, or load-only V2G, where EVs were treated as a controlled load which gives the grid operators more flexibility in charging EVs during peak hours by postponing the charging process to other times where loads are low. This type is called V1G in some papers [8]. The second one was bidirectional V2G, or regular V2G, which allows EVs to charge and discharge their batteries and supply the grid with power. Since U.S. Department of Transportations statistics showed that an average vehicle spends 75% of its time parked at home, both V2G types are done while the car is parked, which is both logical and doable .

The concept of V2G has a great potential in electricity markets for providing different services [9], [10]. In [9], the usage of EV fleet that uses V2G concept to provide regulation services was economically evaluated. Other studies suggested that V2G can be used for other services like demand side management (DSM) and providing base energy [11],[12].

Regulation service provided by V2G is considered as the most promising service that can be introduced to the electricity market [13] ,[14]. It is expected that unidirectional V2G will be implemented first due to practical reasons, like the ability of all already existing EVs to participate and provide ancillary services without any additional hardware, the customers' concerns about discharging their batteries, and effect of discharging on the batteries life time [15]. However, unidirectional V2G has many limitations; it has less capability of providing regulation and spinning reserve services. Also, the participation time is reduced if the battery is fully or almost fully charged. These factors affect the amount of profits that can be made by unidirectional V2G . Using bidirectional V2G can help the grid considerably during peak hours.

A single EV undoubtedly can not participate in wholesale energy markets since it does not have enough capacity to do so. The concept of aggregators was first introduced in [12]. The aggregator is an intermediary between the EV owners and the independent system operator (ISO). The aggregator can help the EV owners to participate efficiently in the electricity market and, in the same time, help the ISO in supporting the grid. The need for the aggregator stems from the fact that the capacity of any individual EV is too small to affect the grid. Also, this small capacity is not suitable for bidding in most electricity markets [16]. Aggregation also decreases the forecasting uncertainty of the available power in each hour

[17]. The aggregator gives more flexibility for EV owners who participate in the electricity market because some owners may have some circumstances that force them to leave during their commitment towards the market. Other possible benefits of aggregators for both EV owners and electric grid are discussed thoroughly in [16],[18].

1.2 Thesis Objectives

Based on the aforementioned discussions, this thesis presents respective studies around EV charging and wind power into the smart grid framework, each with a different focus.

Contribution 1, applies game theory to solve the charging scheduling problem in a distributed fashion. The centralized solution can be considered the optimal choice for a small number of EVs; however, the main drawback is the computational limitations when the number of vehicles becomes large. Decentralized methods offer an alternative way to solve the scheduling task by reformulating the problem into smaller subproblems. However,the convergence of the decentralized methods to a unique solution must be guaranteed. In this study, a game-theoretic approach is applied to balance the generation/demand of a virtual power plant with intermittent power unit, i.e., wind power. Scheduling the charging of the EVs is formulated as a game, each EV acts as a player. The equilibrium which ensure the convergence of the solution is proved.

Contribution 2, a market framework for virtual power plant operator (VPPO), which acts as EVs aggregator, and owns wind and thermal generators was proposed. The aggregator aims to maximize its profit which he gains from bidding energy amounts in the day-ahead (DA) market. The optimal bidding strategy combined with controlling the V2G assets under the uncertainty of the wind output, energy prices, imbalance prices, and demand. On the contrary of the recent models, the uncertainties is modeled using the robust optimization (RO) where the decision maker takes his decision under the worst case scenario of the uncertain parameters. A case study and simulation is conducted to reflect the effectiveness of the proposed model. The robust model is compared to the deterministic model, the results show that the robust model under uncertainties give profits which is relatively close to the deterministic model.

1.3 Thesis Outline

The remainder of the thesis is organized as follows.

Chapter 2 provides a literature review of relevant research work which is provided on the wind power trading problems in the electricity market and the aggregation of the EVs' energy and the impact of the combined trading of both in the market.

In Chapter 3, a new model for solving the charging scheduling problem in a distributed fashion is introduced. Decentralized methods offer an alternative way to solve the scheduling task by reformulating the problem into smaller subproblems. However, the convergence of the decentralized methods to a unique solution must guaranteed. Moreover, Exploiting the charging process to provide another services to the grid is a benefit. In this study, a game theoretic approach is applied to balance the generation-demand of a virtual power planet with intermittent power unit i.e., wind power. Scheduling the charging of the EVs is formulated as a game where each EV acts as a player. The equilibrium which ensure the convergence of the solution is proofed. Furthermore, a closed form solution for the Nash equilibrium (NE) of the game was analytically obtained. Simulation over real data is done to verify the proposed model and it's closed form. The simulation results show that the proposed framework is effective in balancing the wind generation with the connected load and beneficial for both the virtual power plant operator and the EVs' owners.

In Chapter 4, a market framework for virtual power plant operator (VPPO), which acts as EVs aggregator, and owns wind and thermal generators was proposed. The aggregator aims to maximize his profit which gains from bidding energy amounts in the DA market. The optimal bidding strategy combined with controlling the V2G assets under the uncertainty of the wind output, energy prices, imbalance prices, and demand was proposed. On the contrary of the existing models, the uncertainties were modeled using the robust optimization (RO) where the decision maker takes its decision under the worst case scenario of the uncertain parameters. A case study and simulation is conducted to reflect the effectiveness of the proposed model. The robust model is compared to the deterministic model, the results show that the robust model under uncertainties give profits which is relatively close to the deterministic model.

Finally, in Chapter 5, the main conclusions of the thesis and some possible future research directions were summarized.

CHAPTER 2

LITERATURE REVIEW

In this chapter, we introduce a detailed literature review of relevant research work which is provided on the wind power trading problems in the electricity market and the aggregation of the EVs' energy and the impact of the combined trading of both in the market.

2.1 Game Theory - An overview

Game Theory (GT) is defined as the art of study and analysis of conflict or cooperation [19]. It provides the theoretical framework for optimization-based distributed control algorithms. The three main components of the game theory are:

- **Players**: the decision makers, where each one wants to maximize a certain objective by taking the best available action.
- **Strategies**: the set of actions that the player may take to achieve its ob-

jective.

- **Payoffs**: the benefits that the player gains after each player plays its action.

Concerning the relation with the time, the games are classified as static and dynamic. In static games all the players take their decisions simultaneously, and the time has no effect on their payoffs. On the other hand, dynamic games where one player has all the information about the actions of the others, he can play more than one time, that the time is playing the main role in the process of decision-making. From another point of view, the games can be categorized into non-cooperative games, where there is no communication between the players and each player acts to maximize his own utility, and cooperative games where the players communicate with each other and plan for maximizing the overall benefit. The solution of the game is known as Nash Equilibrium (NE) and defined as the state where none of the players would have an incentive to deviate unilaterally [20], [21] , [22].

In Section (2.2) we are going to explore the employment of game theory in different smart grids folds.

2.2 Game-theoretic Models into Smart Grids

2.2.1 Demand Side Management with Game Theory

The reliability of the power grids is very crucial. In smart grids, the penetration of renewable energy resources, the evolution of modern control, may decrease the reliability of the system. The demand side management (DSM) plays an important role to solve this problem. The primary role of DSM is to match the generation of the utility to the demand of the customers. Therefore, the objectives of many of the research problems is to minimize the cost of generation, achieve proper PAR, and maximize social welfare. DSM is classified into price-based (smart pricing) and incentive-based (i.e. direct load control (DLC)) techniques. The former one relies on designing pricing policies for the customers to provide the incentives to change their consumption by reduction or shifting using energy consumption schedules (ECS). Many pricing techniques are used such as teal-time pricing (RTP), time of use (TOU), and day-ahead pricing (DAP) [23], [24], [25], [26].

Bu et al. [23] argue that many of the researchers in DSM rely on the assumption that the price of energy and the arrival distribution of demand is already known before, which is not actually practical. So they introduce a stochastic model to control the loads. The authors modelled their algorithm in two stages. At the first stage, Markov decision process was used to formulate the real-time load scheduling, then a learning algorithm was used in the second stage to reduce the amount of needed information for the making decision process. The algorithm reveals a remarkable performance with 30% better than the other learning algorithms exists in the literature.

Li et al. [25] proposed a game model between the retailer and the users as a four stages Stackelberg game. At the first stage the retailer playing as a leader decides on the source of energy to be used, at the second stage the retailer decides on the amount of energy needed, and the price of energy is decided at the third stage. The users, who play as followers, decide on their energy needs to maximize their payoffs at the last stage of the game. The equilibrium of the game is obtained using backward induction to verify the direct benefits for both parties of the game.

Mondal et al. [27] proposed an auction game. The authors merged the minimization of generation cost and the maximization of social welfare into one function, which was solved in two stages. In the first phase, convex optimization model was used to find the minimum generation cost. In the second phase, the generated optimal load was used with Vickrey auction to solve the maximum social welfare. As the untruthful bidding is a common problem with the auction games, the authors introduced the reserve price and studied the Bayesian Nash equilibria to overcome the collusive actions by the customers.

2.2.2 Micro-grids with Game Theory

Micro-grids can be defined as a group of distributed energy sources that located to serve a small geographical areas. Micro-grids may work in isolated mode (island mode), or connected to other MGs or connected to the macro-grid.

Saad et al. [28] introduced the micro-grid (MG) concept that was connected to other distributed energy resources, such as solar panels and wind turbines. They modelled the network as a coalition game with the coalition consisting of a number

N of MGs. The players can cooperate with each other to sell or buy energy inside the coalition while the one that will sell energy outside the coalition firstly will be excluded. The game was constrained by the capacity of each network and the power losses in distributed power lines. The authors concluded the paper by introducing the collaborative model that yields a significant reduction in terms of power loss over the non-cooperative model.

2.2.3 Overview of Electric Vehicle into Smart Grids

Due to the high intermittency of renewable energy sources (RES's), the EVs is a promising solution for the imbalance problem in the smart grid system. In peak hours, the generation of the grid is not enough to meet the demand of the users. In off-peak hours the grid has excess power since the demand (load) is less than the generation. The balancing between the generation and the load is very crucial for the smart grid. EVs can provide this service by the meaning of V2G.

Han et al. [9], the authors discussed the problem of EVs that plugged in with high SOC, they can't discharge till the regulation up signal is provided by the utility; consequently, the profit of the aggregator will be decreased. Uneven distribution of the regulation capacity between the EVs will guarantee to maximize the profit of the aggregator with providing the requested regulation signal. The problem modelled as a Quadratic program under energy constraints. The authors did not consider the unexpected departure of the EV.

Lam et al. [29] , [30] discussed the problem of estimation the capacity of the aggregator. The authors modelled the regulation up capacity and regulation down capacity separately. Using Queuing theory the EV's was arranged according to their state of charge. Then the capacity normalized to the number of EV's in each queue. Smart charging mechanism was designed in the extended version.

Lee et al. [31] proposed a model of charging station which is authorized to provide the regulation service for individual vehicles in a centralized fashion. Each vehicle needs to be charged to the upper limit of the state of charge (SOC) before the next departure time. This process is not easy to achieve because charging an electric vehicle battery takes larger time than filling a vehicle gas tank, which can be accomplished in a few minutes. Charging a battery usually requires from one to several hours, depending on the current SOC, the number of the available charging inlets at the station, and the line capacity.

Sortomme et al [14] , [32]. proposed the problem of controlling the V2G assets to provide regulation and ancillary services form the aggregator point of view. The objective was to maximize the aggregator's profit who providing ancillary services to the market by controlling the charging rate of the EVs. Basically, the aggregator schedule the EVs to a certain point preferred operating point (POP) and the increase or reduction from this schedule facilitate the aggregator to provide services for the grid.

2.3 Wind Balancing and Demand-side Management

Balancing the generation-load profile in the smart grid is an essential requirement. However, this is not an easy task with integrating RES specially the wind power due to its variability and stochastic nature [33]. Recently, researchers have tackled this problem by considering flattening the generation-load curve by balancing the wind generation. Usually, this was done using conventional (thermal) generators. Al-Awami et al. [34] used a mixed-integer stochastic linear program (MILP) model to optimize the coordinated trading of thermal and wind generation. The objective was to maximize the expected profit of the generation companies by obtaining the optimal bidding strategy in the electricity markets under wind uncertainty. The uncertainty of the wind was controlled using the conditional value at risk to maximize the worst case scenario or the scenario with the least profits. the simulation results show that the coordination between the thermal generators and wind can increase the expected profits even under the considered risk of several uncertainties.

Asensio et al. [35] proposed a model for the day-ahead market trading of the wind power producer and the demand response aggregator. the authors aimed to maximize the expected profit of the wind power producer using a scenario-based optimization model to deal with the uncertainties of the available wind power and the market prices. the conditional value at risk was used to represent the level of the uncertainty for the decision maker. the risk of the uncertainties was reduced and the expected profit was increased as shown by the simulation results.

Qiu et al. [36] used energy storage system (ESS) and a strategy for sharing the risk by the concept of insurance to reduce the imbalance cost of the wind generation. However, this solution is not favourable due to the high cost of implementing the ESS.

2.3.1 Electric Vehicles as Source of Wind Balancing

Recently, EVs have received massive interest from the general public because of its significant role to reduce the environmental impacts of using fossil fuel and to achieve energy independence. EVs have many benefits compared to the conventional combustion engine vehicles such as fast response and lower operating costs. Integrating EVs into the power grid with RES to mitigate their intermittent is the main purpose behind V2G. Exploiting the EVs in balancing the wind generation by controlling the charging and discharging operations has been addressed in some research papers.

Yifan et al. [37] used a multi-stage stochastic model to integrate the EVs with RES i.e., wind power as a source for balancing and an efficient way for mitigating the risks. The optimal power flow in tow different cases was studied. the first case without using the EV fleet, and the second case with the EV fleet is involved. The simulation results show the effectiveness of the EVs as an alternative for the thermal generators in terms of reducing the system costs. However, optimizing the V2G assets was not considered in this research.

Vandael et al. [38] proposed a tree model of the system operator (SO), the EVs aggregator, and the EVs owners where two strategies for the distributed charging was introduced, EVs reactive and proactive strategy. The latter considers dividing the imbalance costs equally over the time span, while the former can be used when the imbalances can be postponed. However, the last strategy requires a small prediction errors.

Mets et al. [39] used a centralized model where the aggregator of the EVs has a full control over the charging/discharging process for comparison with the decentralized model. The distributed problem was modelled using the dual decomposition of the main optimization problem into a small sub-problems where each EV solves its own problem to minimize the mismatch between the wind generation and the demand.

Pillai et al. [40] discussed the impact of using the EVs as a source of DSM when the wind power is integrated into the gird with different levels. the results show that approximately 10% of the total vehicle fleets running in Denmark may be transformed to EVs to supply the balancing power requirements of integrating 50% wind power generation.

2.3.2 Wind Balancing and EV Charging Using Game Theory

To optimally schedule the EV charging process; a large scale optimization problem may be present. As the number of vehicles is increased, the computation costs will expand disastrously. A centralized control may not be the proper method with such computational requirements. For such situations, decentralized control should be developed. Decentralized solutions, in contrast with centralized ones, aims to divide a large problem into a number of simpler sub-problems where the solution for each sub-problem can be found by different agents. Each agent is responsible for computing his part of the problem [41], [42]. Communications between different agents is allowed whenever needed to share information. One of the most prominent decentralized method is game theory which has drawn significant attention in the last years [43].

By nature, the charging scheduling of the EVs can be easily formulated as a game. However, only a few papers have addressed the problem of balancing the wind generation by exploiting EVs from the perspective of the game theory.

Wu et al. [44] studied the demand side management jointly with the wind generation balancing problem. Reducing the imbalance costs of the grid caused by the fluctuation in wind generation was done by the demand-side resources such as EVs, energy storage systems (ESS),..etc. The game model was proposed such that the payoff of the players was a function of the energy price, which in turn was a function of the imbalance.

Wu et al. [45] aimed to balance the wind power using EVs. A Stackelberg game was modelled between the wind generation companies and the EVs. Usually, compensating for reactive wind power was done using static var compensator's (SVCs), since the response time of SVCs is considerably slow, using static synchronous compensator's (STATCOMs) is the alternative solution. However, STATCOMs are expensive which indicates that it's not the feasible solution for large systems implementation. Exploiting the EVs to compensate for the reactive wind power was studied.

The payoff of the EVs in the work presented in [44] was a function of the energy price which in turn is a function in the imbalance between the generation and the load. However, its positively biased by the constant base price. In the first part of this work, we formulated the payoff of the EVs as a function of the deduction which in turn is a function of the imbalance. The positive biasing reflects that the value of the objective function at the optimal power draw is always greater than the value of objective function that proposed in our work. Hence, The proposed model guarantees more benefit for the VPPO (i.e., less imbalance) while keeps the payoff of the EVs maximized. Moreover, in [44] the operation constraints of the grid was not completely considered, i.e., the departure and arrival time. Also, in [39] the author did not count the overcharging constraint. Decomposing the centralized problem using dual decomposition in [39] does not guarantee the satisfaction of each EV owner since the decision will not be taken based on the best response of the other EV owners. In other words, an equilibrium might not be reachable.

2.4 Wind Power Trading in Electricity Markets

The optimal trading strategies for the wind power producer (WPP) in the Electricity markets are modelled in tow types. The first type based on the assumption that the WPP acts as a price taker, in this model the WPP behaviour would not affect the market price. The second type based on the assumption that the WPP acts as a price maker where the WPP behaviour will affect the market price and consequently the market equilibrium. However, the decision making process in both modes is based on the stochastic nature of the wind generation, hence the deterministic models for wind generation are not applied. Furthermore, the stochastic model was proven to outperform the deterministic models which built on the forecasting values only in terms of the expected profit and the variability of the profit [46].

Asensio et al. [35] studied the optimal bidding strategy of the wind power producer into the day-ahead market was paired with the demand response. Stochastic optimization model was used to handle the uncertainty in the wind output and the energy prices. The results show that pairing the aggregation of the demand response with the wind even under uncertainty will be beneficial for the wind power producer as the end-user.

Bourry et al. [47] estimated a probability distribution for the imbalance cost of wind power. A risk-based decision approach is used to determine the optimal bidding strategies. The risk is quantified using the value-at-risk (VaR) model.

Dent et al. [48] discussed the bidding strategy of wind power producers with the assumption of continuous probability distribution for wind power. The correlation between real-time price and wind power is also considered in the model.

2.4.1 Wind Power Trading Using Stochastic Optimization

In the last decade, the stochastic optimization raised as the proper modelling tool for wind power trading into the electricity market. In the energy markets framework the decision makers have to make their decisions over a time horizon involves several stages. As example, at the first stage i.e., the day-ahead market, the decisions are made before the realization of the energy prices of the real-time markets. At the second stage, the real-time market decisions are made after the clearing of the day-ahead and before the realization of the real-time market prices. Hence, the stochastic programming is the proper tool for modelling the trading of the wind power in energy markets.

The concept of the stochastic optimization based on the fact that the stochastic process can be represented using a random variables. For the case of the continuous random variables, the solution is feasible over small set of scenarios, the scenarios are built using scenario tree Fig. 2.1.

To capture the exact stochastic nature of the random variable, a large number of scenarios must be generated. Due to the computational burden of the large set, a reduced set need to be generated [49], [50], [51], [52]. Usually, the seasonal autoregressive integrated moving average (ARIMA) is used to generate the scenario tree for the uncertain parameters. Then, a fast-forward scenario reduction

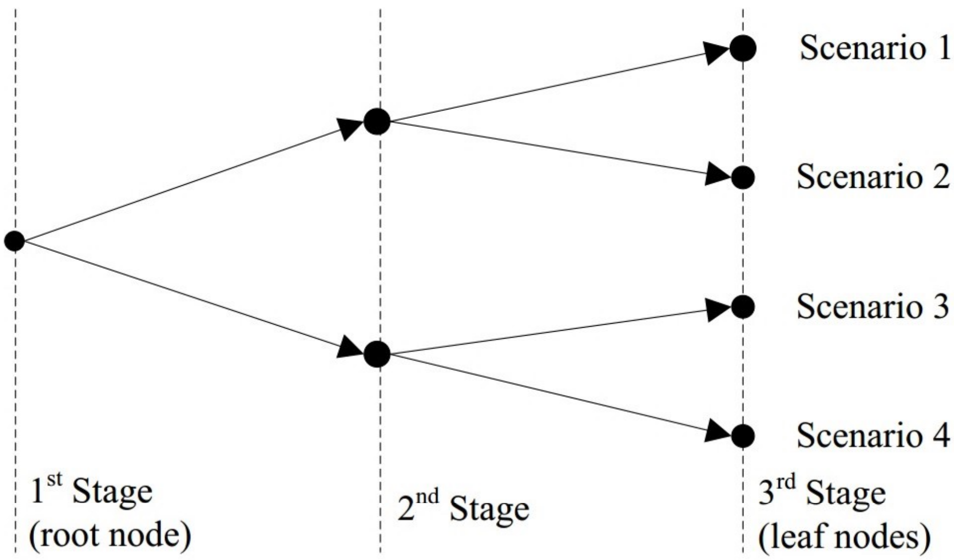

Figure 2.1: Schematic for scenario tree.

algorithm is used to reduce the generated tree [53].

Al-Awami et al. [34] the coordinated trading of thermal generators and wind generators was proposed. They aim to maximize the gained profit form both wind power and thermal power using two stage stochastic programming. The uncertainties of the wind output, energy prices and imbalance prices was modelled using scenarios. the risk of the wind output was mitigated by the coordination with thermal generators.

Morales et al. [46] proposed a model for the wind power trading in day-ahead and real-time markets using linear stochastic programming.

Catalao et al. [54] proposed the optimal bidding of a wind power producer in the day-ahead and real-time markets using two-stages stochastic programming.

CVaR was used as a risk measure for the uncertainties.

2.4.2 Wind Power Trading Using Robust Optimization

The main advantage behind robust optimization is that it offers an optimization approach which does not require a prior knowledge a bout the probability distribution to deal with uncertainty. Instead, dealing with the uncertain parameters is done through the use of an uncertainty set [55]. on the contrary of stochastic programming, which is consider a probabilistic-based optimization approach. In this regard, for many problems in power systems its not an easy task to accurately estimate the probability distribution of the uncertain variable. Moreover, the problem size is hugely increased due to the need of a large number of scenarios to be considered in order to guarantee the solution. Robust optimization solves for the worst case of uncertainty within the uncertainty set, hence the solution is feasible for all realizations of uncertain variables within the given uncertainty set. The other advantage is that for many classes of optimization problems the RO formulation is tractable [56].

Robust optimization was extensively discussed in models such as unit commitments (UC) and security constrained unit commitment (SCUC) models when the decision maker faced by uncertainty in energy prices or/and output of another intermittent generator such as wind.

Zeng et al. [57] the UC problem was formulated as a two stage model, at the first stage the scheduling of the thermal generators was decided, while at the second stage the economic dispatch of the units and the actual output of the power was decided. The objective function was to minimize the total cost of the system i.e., start-up, in the two stage. Two formulation of the UC problem was proposed the risk constrained and the expanded robust. The work concluded by the results that prove the economic benefits of the robust solution of the UC problem over the opposed scenario based solution.

Zhao et al. [58] the UC problem was coupled with the wind uncertainty and demand response in a two stage problem. Minimizing the total operation cost of the power system was aimed by the authors. The results show that there a significant reduction in the system cost using the proposed robust UC model.

Wang et al. [59] The concept of the adjustable uncertainty set was newly introduced. The problem of the robust risk-constrained UC was formulated as two level problem, the decomposition method was used to solve the optimization problem when the the sub-problem was solved for certain values for the decision variables of the master problem. Then, the relaxed master problem is solved based on the convergence of the sub-problem. The objective is to minimize the total operation cost of the system. Although the results show that the model is effective in reducing the cost, the proposed model is hardly applicable in the current energy market structure.

Coordination of the wind power with another sources of power to mitigate the risks and to handle the uncertainty under the robust optimization umbrella was also proposed in the literature.

Thatte et al. [60] used the conditional value at risk (CVaR) as a risk measure linked with the uncertainty set of the robust model to optimally bid the wind power coordinated with storage system. Maximizing the profit of the wind power producer was aimed under the uncertainty of the wind and the energy prices.

Lima et al. [61] and Jiang et al. [62] proposed the coordination with hydro power generators. In [61] a two stage robust model was formulated. Maximization the profit of the virtual power plant operator gained from the forward contracts and the day-ahead market was proposed. Bender's decomposition was used to facilitate the solution of the min-max problem which reformulated as MILP problem. The results show that the proposed robust model was effective to mitigate the risks of the wind output and the prices and to maximize the profit.
Although the effectiveness of the thermal generators as a source of wind power balancing, the need for a more flexible source which matches with both positive and negative imbalances with no extra cost is raised. Exploiting the V2G services through the EVs considers the most suitable solution for such a case [15].

Melo et al. [63] propose a robust model for aggregating the EVs under the uncertainty of the arrival and departure time coupled with the energy prices' uncertainty. The robust optimization approach for optimal scheduling of the VPP and the optimal bidding strategy under the energy price's uncertainty was proposed in [64] and [65] respectively.

Al-Awami et al. [15] proposed a model for a load service entity (LSE) with wind and thermal generators. The coordination between the wind-thermal generators and the EVs was proposed as a source of risk mitigation and controlling the uncertainness resulted from wind output and energy prices. The problem was formulated as a stochastic mixed-integer linear program. The objective was to maximize the aggregators profit. A case study for the Spanish driving behavior was conducted. The results show the high impact of the EVs in maximizing the profits. Furthermore, the environmental effect of integrating the EVs was clearly evident.

According to the previous discussion, few papers discussed the coordination between wind-thermal generators and EVs using the robust approach for dealing with uncertainties, which motivates us to provide the contribution of this work.

2.5 Summary

This chapter gives a brief literature review of different methods and models which have been used for combined integration of the wind power and the electric vehicles into the smart grids. It started with the researches which discussed the problem of balancing the wind generation with the load. Balancing the wind generation by using different technologies such as ESS and thermal generators were discussed. Then we continued with the models which used the EVs as a balancing source from various perspectives, game theoretic models had the special attention. Trading the wind power in the electricity markets under the uncertainty of generation and energy price was reviewed. The stochastic programming was the most used tool to model the uncertainties. However, using the robust optimization to model the uncertainty of trading the wind power and electric vehicles was rarely discussed in the literature.

CHAPTER 3

INCENTIVE-BASED GAME THEORETIC APPROACH FOR WIND POWER BALANCING USING ELECTRIC VEHICLES

In this chapter, a novel model for solving the EVs charging scheduling problem to balance the generation with demand in a distributed fashion was proposed. Decentralized methods offer an alternative way to solve the scheduling problem by reformulating the problem into smaller subproblems. However,the convergence of the decentralized methods to a unique solution must be guaranteed. Exploiting the charging process to provide other services to the grid is a benefit. In this chapter, game theoretic approach is applied to balance the generation/demand of a virtual power plant with intermittent power unit i.e., wind power. Scheduling the charging of the EVs is formulated as a game, where each EV owner acts as a player. The equilibrium which ensure the convergence of the solution is proved. Furthermore, a closed form solution for the NE of the game is analytically obtained. Simulations of a case study are carried out to verify the proposed model and its closed form solution. The simulation results show that the proposed framework is effective in balancing the wind generation with the connected load and benefits both the virtual power plant operator and the EVs owners.

3.1 Introduction

A major focus toward utilizing the green energy resources is being promoted globally. Wind energy is a very vital resource in this regard. Integration of the wind energy in the power grid has been dramatically increased in the last few years. Despite its major benefits, it has high uncertainty and variability. Therefore, the optimal operation of the power grid and balancing the generation-load profile under these conditions is a huge challenge [33], [60], [66]. EVs have been proven to be one of the promised sources for helping the wind power generation companies to face these challenges. Controlling the EVs charging can be used to provide the required balance for the power grid [15].

3.2 Problem Formulation & System Model

We assume that there is a virtual power plant (VPP) that consists of wind generation units, a parking lot for EVs, and some uncontrollable load. The main responsibility of the virtual power plant operator (VPPO) is to ensure that the energy consumption by the loads is matching with the wind generation. Otherwise, the VPPO is required to pay imbalance costs. Hence, the main objective of the VPPO is to maintain the imbalance as minimum as possible. VPPO exploits the connected EVs as a controllable load to reduce the imbalance taking into account EVs considerations such as arrival time, departure time, and the initial state of charge. Unidirectional mode of charging was considered here, where the discharging (bidirectional mode) is not practically applicable; e.g., it requires advanced hardware implementation or other operational constraints.

Centralized control is not applicable for large number of EVs. Moreover, it gives rise to privacy issues such as sharing arrival and departure times,...etc. Hence, we propose a distributed charging algorithm where each EV decides about the total power draw it consumes from the power grid. The operation constraints for each EV will be respected, and the privacy will be maintained secure.

3.3 Game Theoretic Model

Considering the VPP shown in Fig. 3.1, where a set of N_C EVs, Wind units with power W_t generated at time t, and uncontrollable load of power L_t at time t, are all connected to a control center which is managed by the VPPO. Each EV has

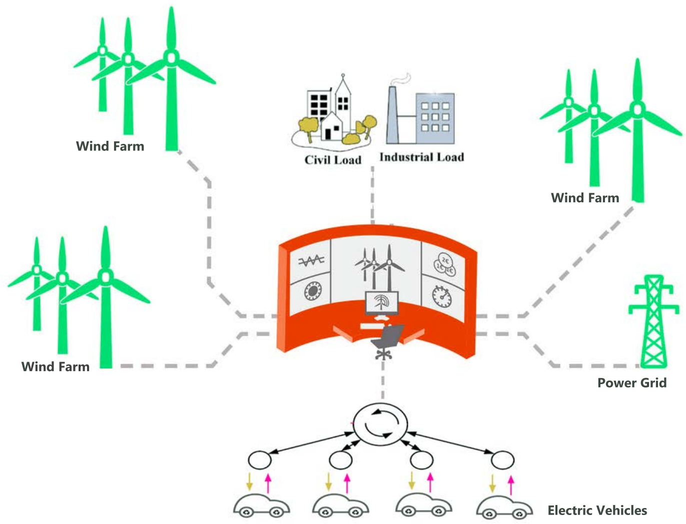

Figure 3.1: Schematic of a virtual power plant.

some constraints which result from either operational or personal requirements. One of the constraints which reflects an individual requirement of the EV owner is that the battery should be charged to a certain percentage before departure in the morning (e.g., 60% of the maximum capacity). On the other hand, the maximum power that can be delivered by the station charger reflects an operational limit for the power drawn by EV c at any time t.

The key idea behind the distributed algorithm is that the mismatch between the generation and the load will be aligned with the EVs behavior through offering the proper incentives. An incentive offered by the VPPO to the participated EVs in the balancing operation can be a deduction from the original offered energy price. Therefore, the payoff of each EV is proportional to the total power drawn by the EV. Define:

$$\lambda_t = \beta \Delta_t, \tag{3.1}$$

as the price deduction per Kilowatt (KW), where

$$\Delta_t = W_t - L_t - \sum_{c=1}^{N_C} PD_{c,t} \quad , \tag{3.2}$$

defines the mismatch between the generation (W_t) and the load ($L_t + \sum_{c=1}^{N_C} PD_{c,t}$) at time slot t. We define $PD_{c,t}$ as the power draw of EV c at time slot t, and β is a positive design parameter in ($cent/KW^2$) which is chosen by the VPPO to align the mismatch with the offered deduction.

Since the EVs owners are independent decision makers, some EVs might want to provide balancing services to the grid, while some other EVs might not have the intention to provide any services. This conflict may result in formulating a game between the EVs. The wind balancing game (*WBG)* is initiated between the EVs to maximize their shared payoff by maximizing the offered incentive (discount) by the VPPO.

3.3.1 EVs Game

The game among the EVs (WBG) can be constructed as:

- Players : the set N_C of all the EVs.
- Strategies : based on the incentive given by the VPPO, the c^{th} EV decides

about its PD_c, given the information of MC_c as the maximum charging capacity for each EV c , $MP_{c,t}$ as the maximum power drawn by the charging station outlet for each EV c at each time t, and SOC_{I_c} as the initial state of charge for each EV c.

- Payoff : the payoff function of each EV is defined in Section 3.3.2.

3.3.2 EVs pay-off

The payoff function for each EV can be formulated as the total deduction that the EV gains. That is, for EV $i \in N_C$, the payoff function at a certain time slot is:

$$\begin{aligned} f_{i,t}(PD_{c,t}, PD_{-c,t}) &= \lambda_t PD_{c,t} = (\beta \Delta_t)\, PD_{c,t} \\ &= \left(\beta \left(W_t - L_t - \sum_{c=1}^{N_C} PD_{c,t}\right)\right) PD_{c,t} \\ &= \big(\beta\big(W_t - L_t - \sum_{m \in N_C \setminus \{c\}} PD_{m,t}\big)\big) PD_{c,t} - \beta PD_{c,t}^2 \quad , \end{aligned} \tag{3.3}$$

where $PD_{-c,t}$ is the set of power draws of all EVs other than the c^{th} EV, at time t. Therefore, the payoff of each EV is a function of all other EV responses which leads to the proposed game.

3.3.3 Best Response and Nash Equilibrium

The NE of the WBG will be obtained using the best response strategy, which is defined as the power draw of each EV that maximizes its own payoff function assuming that all other EVs power draw amounts are fixed. For each EV $c \in N_C$, the best response is:

$$PD_{c,t}^{best}(PD_{-c,t}) = arg \max_{PD_{c,t}} f_{c,t}(PD_{c,t}, PD_{-c,t}) \ ,$$
$$= arg \min_{PD_{c,t}} \Big(\big(-\beta\big(W_t - L_t - \sum_{m \in N_C \setminus \{c\}} PD_{m,t}\big)\big) PD_{c,t} + \beta PD_{c,t}^2 \Big) \,. \tag{3.4}$$

Therefore, the main objective function of each individual EV is:

$$\min_{PD_{c,t}} \big(-\beta\big(W_t - L_t - \sum_{m \in N_C \setminus \{c\}} PD_{m,t}\big)\big) PD_{c,t} + \beta PD_{c,t}^2 \tag{3.5}$$

subject to ,

$$Av_{c,t} \left(\frac{0.6MC_c - SOC_{I_c}}{T_{d,c} - T_s} \right) \leq PD_{c,t} \quad , \forall \ c, t \in \{T_s, ..., T_{d,c} - 1\} \tag{3.6}$$

$$PD_{c,t} \leq MC_c - SOC_{I_c} - \sum_{s=1}^{T-1} PD_{c,s} \ \forall \ c, \tag{3.7}$$

$$0 \leq PD_{c,t} \leq MP_{c,t} \times Av_{c,t} \ \forall \ c, t \quad , \tag{3.8}$$

where $Av_{c,t}$ is the availability of EV c at time t for charging, $T_{d,c}$ is the departure time of each EV c, and T_s is the time which the simulation is considered to be started.

Constraint (3.6) guarantees that the each EV will be charged to a certain level (in this paper we consider it to be 60% of the full capacity) before the departure time in the morning. Constraint (3.6) is designed to divide the charging percentage equally. To prevent any degradation for the EV battery caused by over charging, EV owners limit the amount of the charged energy by (3.7). Constraint (3.8) limits the power draw by each EV to the maximum allowable power draw from the station charger (i.e., MP) whenever the EV is available. The lower bound is zero here to demonstrate the unidirectional charging mode. These constraints define a feasible set for the charging schedule. This feasible set is denoted by ϕ_c for EV $c \in N_C$. Then, we define Nash Equilibrium as the vector of all players' strategies such that no player has an incentive to deviate unilaterally.

$$f_{c,t}(PD^*_{c,t}, PD^*_{-c,t}) \geq f_c(PD_{c,t}, PD^*_{-c,t}) \quad \forall c \in N_C, \forall\, PD_c \in \phi_c$$

A Nash equilibrium is a fixed point of all players' best responses, $(i.e., PD^{best}_{c,t}(PD^*_{-c,t}) = PD^*_{c,t})$ for all $c \in N_C$, which provides a stable solution of the game.

Thoerem: The Nash equilibrium for the WBG always exists and it's unique.

proof: The proof is given in the appendix.

3.3.4 Iterated Best Response (IBR) Algorithm

We assume that the distributed algorithm is running by the EVs at each time slot t such that:

- Initialization phase

  - The VPPO predicts the wind generation and the load forecasts for each time slot t.

  - The VPPO announces the energy price and the deduction for each time slot t which satisfies its requirements by matching the generation with the load.

- Execution phase

  - At the beginning of each t each EV owner computes its power draw according to the announced deduction, and submit it back to the VPPO, considering the best responses of other EVs.

  - The VPPO collects the submitted power amounts and computes the generation/load mismatch, if it was below a certain predefined level, or a maximum number of iterations is reached, the algorithm terminates and the power amounts are final.

  - Otherwise, the VPPO updates the deduction and the algorithm is repeated.

3.3.5 Karush-Kuhn-Tucker (KKT) Optimality Conditions

The Lagrangian function and KKT conditions for the EVs payoff maximization nonlinear program can be written as :

$$
\begin{aligned}
L = & \Big(-\beta\big(W_t - L_t - \sum_{m\in N_C\setminus\{c\}} PD^*_{m,t}\big)\Big)PD_{c,t} + \beta PD^{*2}_{c,t} \\
& + \alpha_{1_{c,t}}(PD^*_{c,t} - MC_c + SOC_{I_c} + \sum_{s=1}^{T-1} PD^*_{c,s}) + \alpha_{2_{c,t}}\left(\frac{0.6MC_c - SOC_{I_c}}{T_{d,c} - T_s} - PD_{c,t}\right) \\
& - \alpha_{3_{c,t}} PD^*_{c,t} + \alpha_{4_{c,t}}(PD^*_{c,t} - MP_{c,t}) \quad , \qquad (3.9)
\end{aligned}
$$

where $\alpha_{k_{c,t}}$ is the Lagrangian multiplier associated with each constraint. The KKT optimality conditions are given as:

$$
\begin{aligned}
\frac{\partial L}{\partial PD^*_{c,t}} = & \Big(-\beta\big(W_t - L_t - \sum_{m\in N_C\setminus\{c\}} PD^*_{m,t}\big)\Big) + 2\beta PD^*_{c,t} \\
& + \alpha_{1_{c,t}} - \alpha_{2_{c,t}} - \alpha_{3_{c,t}} + \alpha_{4_{c,t}} = 0, \ \forall c \in N_C, t. \qquad (3.10)
\end{aligned}
$$

$$
\begin{aligned}
& - PD^*_{c,t} \le 0, \ PD^*_{c,t} - MP_{c,t} \le 0 \quad \forall c, \ t, \\
& PD^*_{c,t} \le MC_c - SOC_{I_c} - \sum_{s=1}^{T-1} PD^*_{c,s} \quad \forall c, \\
& PD^*_{c,t} \ge \left(\frac{0.6MC_c - SOC_{I_c}}{T_{d,c} - T_s}\right) \quad \forall \quad c, \quad t \in \{T_s, ..., T_{d,c}\}. \qquad (3.11)
\end{aligned}
$$

$$\alpha_{1_{c,t}} \geq 0, \quad \alpha_{2_{c,t}} \geq 0, \quad \alpha_{3_{c,t}} \geq 0 \quad \alpha_{4_{c,t}} \geq 0 \quad \forall c, t. \tag{3.12}$$

$$\alpha_{3_{c,t}} PD^*_{c,t} = 0, \quad \alpha_{4_{c,t}} (PD^*_{c,t} - MP_{c,t}) = 0 \quad \forall c \in N_C, \tag{3.13a}$$

$$\alpha_{1_{c,t}} (PD^*_i, t - MC_c + SOC_{I_c} + \sum_{s=1}^{T-1} PD^*_{c,s}) = 0, \tag{3.13b}$$

$$\alpha_{2_{c,t}} (\frac{0.6MC_c - SOC_{I_c}}{T_{d,c} - T_s} - PD^*_{c,t}) = 0. \tag{3.13c}$$

Now, we are going to examine the different possible cases for the optimal power draw using KKT optimality conditions.

1. $\alpha_{1_{c,t}} = \alpha_{2_{c,t}} = \alpha_{3_{c,t}} = \alpha_{4_{c,t}} = 0$,

   from (3.9) it can be seen that:

$$PD^*_{c,t} = \frac{\left(W_t - L_t - \sum_{m \in N_C \setminus \{c\}} PD^*_{m,t}\right)}{2} \quad . \tag{3.14}$$

2. $\alpha_{1_{c,t}} = \alpha_{2_{c,t}} = \alpha_{3_{c,t}} = 0, \alpha_{4_{c,t}} > 0$,

   from (3.13a), when $\alpha_{4_{c,t}} > 0$, then $PD^*_{c,t} = MP_c$,

   $\alpha_{4_{c,t}} = -\beta(W_t - L_t - \sum_{m \in N_C \setminus \{c\}} PD^*_{m,t}) \quad .$

3. $\alpha_{1_{c,t}} = \alpha_{2_{c,t}} = \alpha_{4_{c,t}} = 0, \alpha_{3_{c,t}} > 0$,

   from (3.13a), when $\alpha_{4_{c,t}} > 0$, then $PD^*_{c,t} = 0$, $\alpha_{3_{c,t}} = -\beta(W_t - L_t - \sum_{m \in N_C \setminus \{c\}} PD^*_{m,t}) \quad .$

4. $\alpha_{1_{c,t}} = \alpha_{2_{c,t}} = 0, \alpha_{3_{c,t}}, \alpha_{4_{c,t}} > 0$,

   from (3.13a), when $\alpha_{4_{c,t}} > 0$, then $PD^*_{c,t} = MP_c$, $\alpha_{3_{c,t}} > 0$, then $PD^*_{c,t} = 0$, contradiction, infeasible solution.

5. $\alpha_{1_{c,t}} = 0, \alpha_{2_{c,t}}, \alpha_{3_{c,t}}, \alpha_{4_{c,t}} > 0$,

   from (3.13a), when $\alpha_{4_{c,t}} > 0$, then $PD^*_{c,t} = MP_c$, $\alpha_{3_{c,t}} > 0$, then $PD^*_{c,t} = 0$, contradiction,infeasible solution.

6. $\alpha_{1_{c,t}} = \alpha_{3_{c,t}} = \alpha_{4_{c,t}} = 0, \alpha_{2_{c,t}} > 0$,

   from (3.13c), when $\alpha_{2_{c,t}} > 0$, then $PD^*_{c,t} = \frac{0.8MC_c - SOC_{I_c}}{T_{Dep}}$.

7. $\alpha_{1_{c,t}} = \alpha_{3_{c,t}} = 0, \alpha_{2_{c,t}}, \alpha_{4_{c,t}} > 0$,

   from (3.13a, 3.13c), when $\alpha_{4_{c,t}} > 0$, then $PD^*_{c,t} = MP_c$, when $\alpha_{2_{c,t}} > 0$, then $PD^*_{c,t} = \frac{0.8MC_c - SOC_{I_c}}{T_{Dep}}$.

8. $\alpha_{1_{c,t}} = \alpha_{4_{c,t}} = 0, \alpha_{2_{c,t}}, \alpha_{3_{c,t}} > 0$,

   from (3.13a, 3.13c), when $\alpha_{3_{c,t}} > 0$, then $PD^*_{c,t} = 0$, when $\alpha_{2_{c,t}} > 0$, then $PD^*_{c,t} = \frac{0.8MC_c - SOC_{I_c}}{T_{Dep}}$.

9. $\alpha_{1_{c,t}} > 0, \alpha_{2_{c,t}} = \alpha_{3_{c,t}} = \alpha_{4_{c,t}} = 0$,

   from (3.13b), when $\alpha_{1_{c,t}} > 0$, then $PD^*_{c,t} = MC_c - SOC_{I_c} - \sum_{s=1}^{T-1} PD^*_{c,s}$.

10. $\alpha_{1_{c,t}}, \alpha_{4_{c,t}} > 0, \alpha_{2_{c,t}} = \alpha_{3_{c,t}} = 0,$

from $(3.13a, 3.13b)$, when $\alpha_{1_{c,t}} > 0$, then $PD^*_{c,t} = MC_c - SOC_{I_c} - \sum_{s=1}^{T-1} PD^*_{c,s}$, when $\alpha_{4_{c,t}} > 0$, then $PD^*_{c,t} = MP_c$.

11. $\alpha_{1_{c,t}}, \alpha_{3_{c,t}} > 0, \alpha_{2_{c,t}} = \alpha_{4_{c,t}} = 0,$

from $(3.13a, 3.13b)$, when $\alpha_{1_{c,t}} > 0$, then $PD^*_{c,t} = MC_c - SOC_{I_c} - \sum_{s=1}^{T-1} PD^*_{c,s}$, when $\alpha_{3_{c,t}} > 0$, then $PD^*_{c,t} = 0$.

12. $\alpha_{1_{c,t}}, \alpha_{4_{c,t}}, \alpha_{3_{c,t}} > 0, \alpha_{2_{c,t}} = 0,$

from $(3.13a, 3.13b)$, when $\alpha_{1_{c,t}} > 0$, then $PD^*_{c,t} = MC_c - SOC_{I_c} - \sum_{s=1}^{T-1} PD^*_{c,s}$, when $\alpha_{4_{c,t}} > 0$, then $PD^*_{c,t} = MP_c$, when $\alpha_{3_{c,t}} > 0$, then $PD^*_{c,t} = 0$, contradiction, infeasible solution because $PD^*_{c,t} = MP_c = 0$ can not occur.

13. $\alpha_{1_{c,t}}, \alpha_{2_{c,t}} > 0, \alpha_{3_{c,t}} = \alpha_{4_{c,t}} = 0,$

from $(3.13b, 3.13c)$, when $\alpha_{1_{c,t}} > 0$, then $PD^*_{c,t} = MC_c - SOC_{I_c} - \sum_{s=1}^{T-1} PD^*_{c,s}$, when $\alpha_{2_{c,t}} > 0$, then $PD^*_{c,t} = \frac{0.8MC_c - SOC_{I_c}}{T_{Dep}}$.

14. $\alpha_{1_{c,t}}, \alpha_{2_{c,t}}, \alpha_{4_{c,t}} > 0, \alpha_{3_{c,t}} = 0,$

from $(3.13b, 3.13c, 3.13a)$, when $\alpha_{1_{c,t}} > 0$, then $PD^*_{c,t} = MC_c - SOC_{I_c} -$

$\sum_{s=1}^{T-1} PD_{c,s}^*$, when $\alpha_{2_{c,t}} > 0$, then $PD_{c,t}^* = \frac{0.8MC_c - SOC_{I_c}}{T_{Dep}}$, when $\alpha_{4_{c,t}} > 0$, then $PD_{c,t}^* = MP_c$.

15. $\alpha_{1_{c,t}}, \alpha_{2_{c,t}}, \alpha_{3_{c,t}} > 0, \alpha_{4_{c,t}} = 0$,

    from $(3.13b, 3.13c, 3.13a)$, when $\alpha_{1_{i,t}} > 0$, then $PD_{c,t}^* = MC_c - SOC_{I_c} - \sum_{s=1}^{T-1} PD_{c,s}^*$, when $\alpha_{2_{c,t}} > 0$, then $PD_{c,t}^* = \frac{0.8MC_c - SOC_{I_c}}{T_{Dep}}$, when $\alpha_{3_{c,t}} > 0$, then $PD_{c,t}^* = 0$.

16. $\alpha_{1_{c,t}}, \alpha_{2_{c,t}}, \alpha_{3_{c,t}}, \alpha_{4_{c,t}} > 0$,

    from $(3.13b, 3.13c, 3.13a)$, when $\alpha_{1_{c,t}} > 0$, then $PD_{c,t}^* = MC_c - SOC_{I_c} - \sum_{s=T_{a,c}}^{T_{d,c}-1} PD_{c,s}^*$, when $\alpha_{2_{c,t}} > 0$, then $PD_{c,t}^* = \frac{0.6MC_c - SOC_{I_c}}{T_{d,c} - T_{a,c}}$, when $\alpha_{4_{c,t}} > 0$, then $PD_{c,t}^* = MP_c$, when $\alpha_{3_{c,t}} > 0$, then $PD_{c,t}^* = 0$, contradiction, infeasible solution.

We can summarize the whole previous possible cases for the solution in the next five cases:

1. $\alpha_{1_{c,t}} = \alpha_{2_{c,t}} = \alpha_{3_{c,t}} = \alpha_{4_{c,t}} = 0$,

   from (3.9) it can be seen that:

$$PD_{c,t}^* = \frac{\left(W_t - L_t - \sum_{m \in N_C \setminus \{c\}} PD_{m,t}^*\right)}{2} \quad . \tag{3.15}$$

2. $\alpha_{4_{c,t}} > 0, \alpha_{1_{c,t}} = \alpha_{2_{c,t}} = \alpha_{3_{c,t}} = 0$,

from (3.13a), when $\alpha_{4_{c,t}} > 0$, then $PD^*_{c,t} = MP_{c,t}$, from (3.10) $\alpha_{4_{c,t}} = \beta(W_t - L_t - \sum_{m \in N_C \setminus \{c\}} PD^*_{m,t})$.

3. $\alpha_{3_{c,t}} > 0, \alpha_{1_{c,t}} = \alpha_{2_{c,t}} = \alpha_{4_{c,t}} = 0$,

   from (3.13a), when $\alpha_{3_{c,t}} > 0$, then $PD^*_{c,t} = 0$, from (3.10) $\alpha_{3_{c,t}} = -\beta(W_t - L_t - \sum_{m \in N_C \setminus \{c\}} PD^*_{m,t})$.

4. $\alpha_{1_{c,t}} > 0, \alpha_{2_{c,t}} = \alpha_{3_{c,t}} = \alpha_{4_{c,t}} = 0$,

   from (3.13b), when $\alpha_{1_{c,t}} > 0$, then $PD^*_{c,t} = MC_c - SOC_{I_c} - \sum_{s=1}^{T-1} PD^*_{c,s}$.

5. $\alpha_{2_{c,t}} > 0, \alpha_{1_{c,t}} = \alpha_{3_{c,t}} = \alpha_{4_{c,t}} = 0$,

   from (3.13c), when $\alpha_{2_{c,t}} > 0$, then $PD^*_{c,t} = \frac{0.6MC_c - SOC_{I_c}}{T_{d,c} - T_s}$.

Its clear that when more than one Lagrangian multiplier is larger than zero either we have a contradiction or an equality. As an example for the contradiction when $\alpha_{3_{c,t}}, \alpha_{4_{c,t}} > 0$ this indicates that $PD^*_{c,t}$ equal to 0 and $MP_{c,t}$ at the same time. While $\alpha_{3_{c,t}}, \alpha_{1_{c,t}} > 0$ is an example for the equality case (i.e., $PD^*_{c,t} = MC_c - SOC_{I_c} - \sum_{s=1}^{T-1} PD^*_{c,s} = 0$).

From the above, the optimum power draw for each EV c at each time t can be given as in (3.16) and (3.17). The NE can be reached by applying the optimal solutions in (3.16) and (3.17) iteratively.

For $t = \{T_s, ..., T_{d,c}\}$

$$PD^*_{c,t} = \begin{cases} \frac{W_t - L_t - \sum_{m \in N_C \setminus \{i\}} PD_{m,t}}{2}, \quad \text{for } \frac{0.6MC_c - SOC_{I_c}}{T_{d,c} - T_s} < \text{this value} < min(MP_{c,t}, MC_c - SOC_{I_c} - \sum_{s=1}^{T-1} PD_{c,s}) \\ \frac{0.6MC_c - SOC_{I_c}}{T_{d,c} - T_s}, \quad \text{otherwise} \end{cases} \tag{3.16}$$

For $t = \{T_{a,c}, ..., T\}$

$$PD^*_{c,t} = \begin{cases} \frac{W_t - L_t - \sum_{m \in N_C \setminus \{c\}} PD_{m,t}}{2}, & \text{for } 0 < \text{this value} < MP_{c,t} \\ MP_{c,t}, & \text{for } MP_{c,t} \leq \text{This value} < MC_c - SOC_{I_c} - \sum_{s=1}^{T-1} PD_{c,s} \\ MC_c - SOC_{I_c} - \sum_{s=1}^{T-1} PD_{c,s}, & \text{for } MC_c - SOC_{I_c} - \sum_{s=1}^{T-1} PD_{c,s} \leq \text{This value} < MP_{c,t} \\ min(MP_{c,t}, MC_c - SOC_{I_c} - \sum_{s=1}^{T-1} PD_{c,s}), & \text{for} \quad \text{This value} > MP_{c,t} \quad \& \quad MC_c - SOC_{I_c} - \sum_{s=1}^{T-1} PD_{c,s} \\ 0, & \text{otherwise} \end{cases} \tag{3.17}$$

3.4 Simulation Results

To assess the efficacy of our proposed model, we assume that the VPP contains one wind generation unit with installed capacity of 1 MW, with the ramping rate of the wind power is modeled as normal distribution with zero mean and standard deviation of 25 KW [15]. We consider a total number of 100 EVs, 16% are BMW-i3, 16% are Nissan-Leaf, 24% as Fiat-500e, and 44% are Mitsubishi. This choice is according to the best selling EVs in USA at 2015 [67, 68]. The specification of each type of the EVs is given in [69, 70, 71, 72]. The initial state of charge for each EV is randomly selected in the range of $(0.1MC : 0.3MC)$, and $\beta = 1$.

The proposed distributed algorithm was compared to the centralized solution when all the data (i.e., arrival time, departure time, initial state of charge,..,etc) are available at the VPPO. The VPPO objective function is given by:

$$\min_{PD_{c,t}} \left(W_t - L_t - \sum_{c=1}^{N_C} PD_{c,t} \right)^2 \tag{3.18}$$

subject to (3.6) - (3.8).

The quadratic objective function models the imbalance cost for the VPPO. Clearly, the convexity of the objective function indicates that the problem can be solved in a centralized approach efficiently.

We consider the scenario of Saudi Arabian driving profile where most of the EV owners leave to work at 8 A.M. (i.e., T_d) and back home at 4 P.M. (i.e., T_a). We assume that the EVs are plugged into the charger only at home, and that not all the EVs will depart nor come back at the same time. Simulation results for one day with one hour as a time slot when 65% of the EVs depart at T_d and 35% remain at home are shown in Fig. 3.2. It can be seen that the behavior of the EVs with a suitable incentive is accurately following the imbalance between the wind generation and the load. However at the beginning of the charging period some of the EVs may not exactly follow the generation/load minimization signal forced by reaching a certain level of charging before the departure time (i.e., $0.6MC$). Comparison between the closed form solution of the NE and the simulated one is also shown in Fig. 3.2, where the provided closed form solution of the game is validated.

In Fig. 3.3, we consider the case when 25% of the EV owners remain at home between T_d and T_a or they choose to depart at other times for different reasons (e.g., shopping, visit,...,etc). Clearly reducing the available number of the EVs between 8 A.M. and 4 P.M. will decrease the chance to satisfy the minimization signal. It's clear that fulfilling the objective (i.e., minimizing the mismatch between generation and load) through these hours is proportional to the number of the available EVs for charging at that time.

Since the most important factor for the EV owner is getting the required level of charging which doesn't conflict with its participation in the balancing game, we plot Fig. 3.4 to show that the final state of charge for a sample of 30 EV at the end of the day is equivalent in both the distributed and the centralized solution.

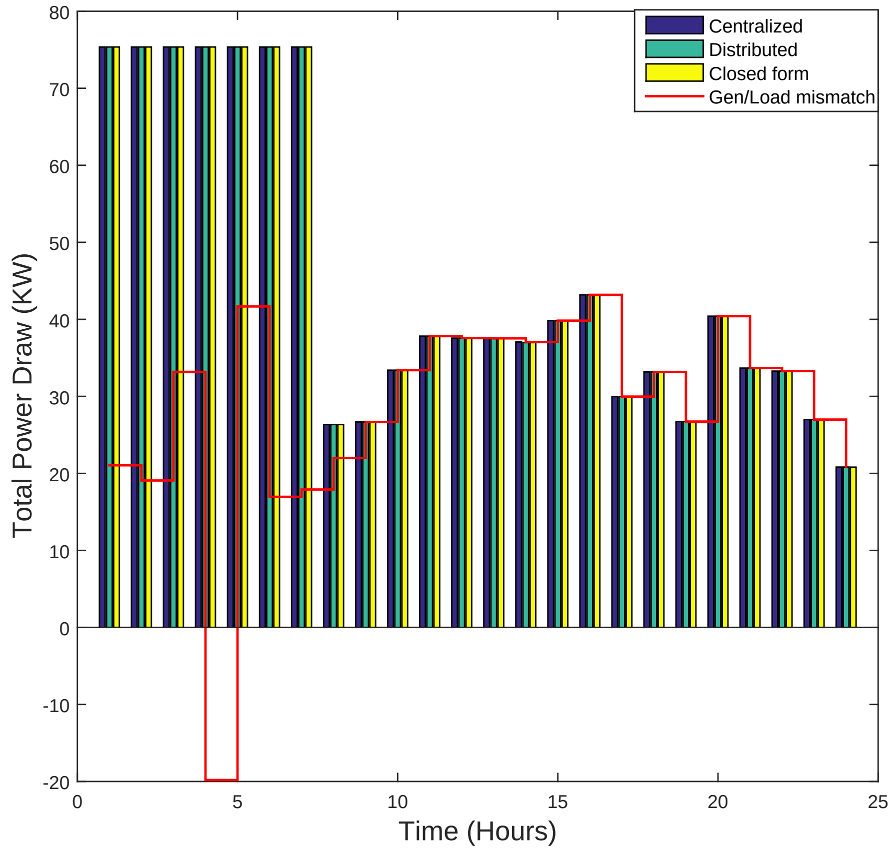

Figure 3.2: One day simulation for 100 EVs with 35% remaining EVs.

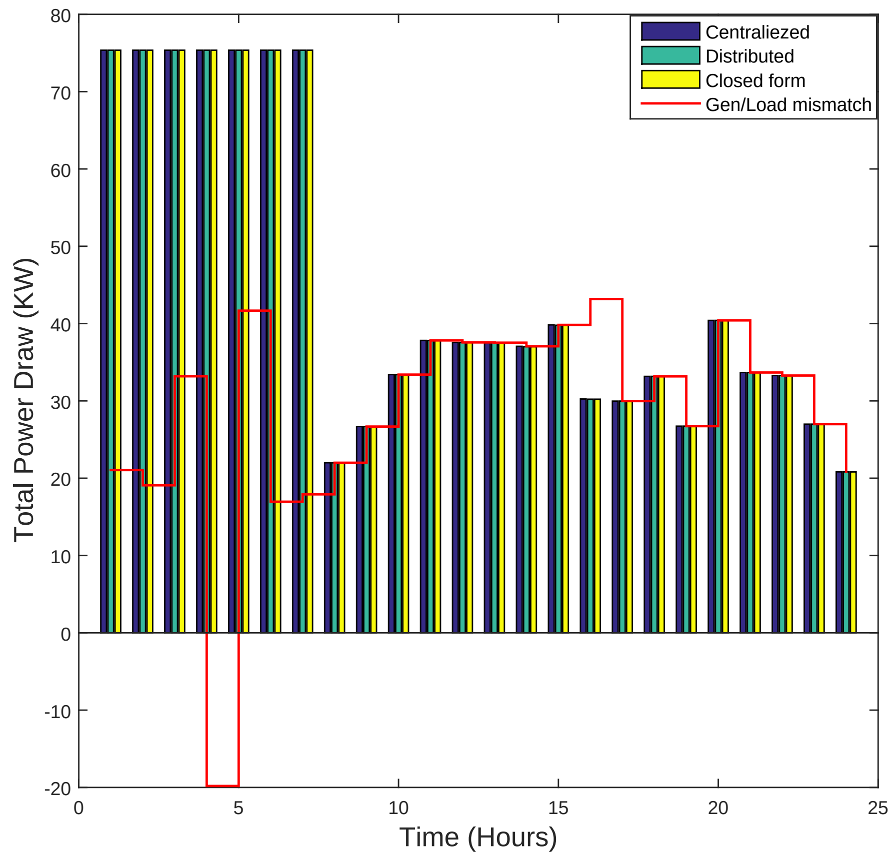

Figure 3.3: One day simulation for 100 EVs with 25% remaining EVs.

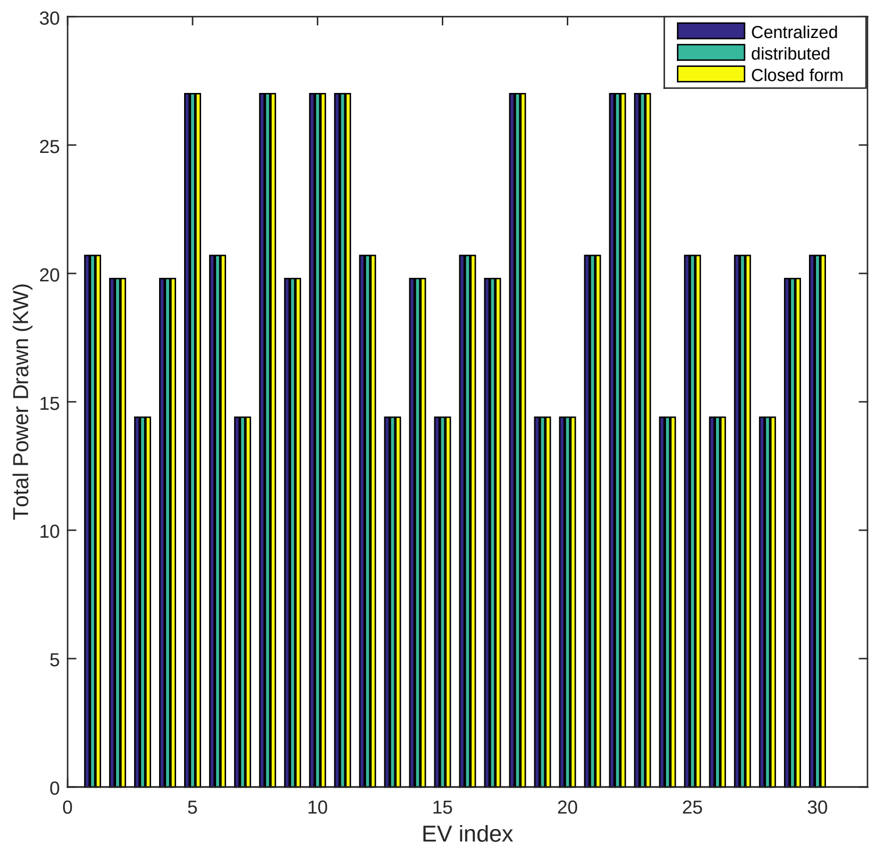

Figure 3.4: Final state of charge (SOC_f) for a sample of 30 EV participated EVs in WBG.

3.5 Conclusion

In this Chapter, the problem of balancing the wind generation with the load in a small virtual power plant as a game theoretic model was addressed. The VPPO coordinate a game between a number of EVs to fulfill the imbalances. An incentive-based scheme to be offered to the EVs where each EV schedule its power draw according to the offered incentive was developed. Furthermore, a closed form solution for the NE of the game was obtained. The distributed model was shown that it can achieve almost the same solution to the centralized one when the EVs are controlled by the VPOO in terms of balancing the mismatch between wind generation and load.

3.6 List of Publications

- **Ahmed M. Abd El-Moaty**, Wessam Mesbah and Ali T. Al-Awami, "Incentive-Based Game Theoretic Approach for Wind Power Balancing Using Electric Vehicles, IEEE 9th Gulf Conference and Exhibition center. (9th IEEE-GCC), Manama, Bahrain, May 2017.

CHAPTER 4

RISK-BASED ROBUST BIDDING STRATEGIES FOR EVS' AGGREGATORS IN DAY-AHEAD MARKETS WITH UNCERTAINTY

In this chapter, we propose a market framework for virtual power plant operator (VPPO) who acts EVs aggregator and owns wind and thermal generators. The aggregator aims to maximize his profit which gains from bidding energy amounts in the day-ahead (DA) market. The optimal bidding strategy combined with controlling the Vehicle-to-grid (V2G) assets under the uncertainty of the wind output, energy prices, imbalance prices, and demand. On the contrary of the recent models, we model the uncertainties using the robust optimization (RO) where the decision maker takes its decision under the worst case scenario of the uncertain parameters. A case study and simulation was conducted to reflect the effectiveness of the proposed model. The robust model was compared to the deterministic model, the results show that the robust model under uncertainties give profits which is relatively close to the deterministic model.

4.1 Introduction

At the last years, the focus of researchers was directed to use the stochastic programming approach to handle the uncertainty in decision making process [49]. However, stochastic programming has been proved to be more computationally challenging due to the need of the large number of scenarios which is indispensable to capture the real nature of the random variable. Furthermore, the complete knowledge of the probability distribution of the random variable is necessary which sometimes not available [73]. Recently. another alternative for the stochastic programming has been attracted the attention of the researchers that is robust optimization. Although robust optimization field is consider relatively young research area. There have been many publications which reflects the advantages of the RO in many of research areas such as finance, energy, supply chain management, circuit design and scheduling problems. The basic concept behind the robust optimization is that it is not a probabilistic model, the uncertainty is handled based on a construction of an uncertainty set where the solution is robust for all the realization of the uncertain parameter within the defined set [74, 75, 56].

4.2 System Model

We assume a small Virtual Power Plant (VPP) with wind generation output $W_{d,t}$ from unit d at time t, thermal units with output $P_{g,t}$ form unit g at time t, a load consisting of two types controllable load such as EVs and uncontrollable load, as shown in Fig. 4.1.

The VPPO is considered a price taker who submits a certain amount of energy

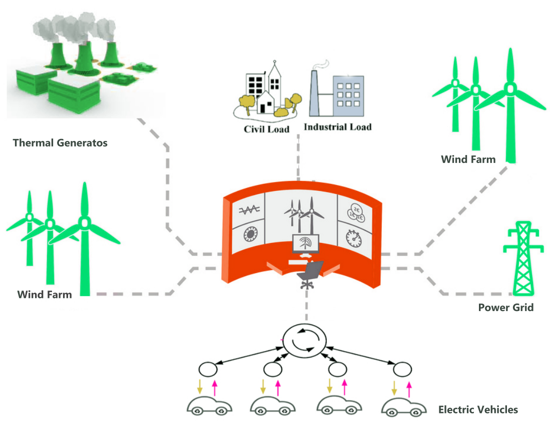

Figure 4.1: schematic of a virtual power plant.

to the day-ahead market 24 hour before the time market clearing process. The VPPO faces uncertainties of the actual wind power, the energy and imbalance prices, and the loads. The coordination between the EVs and thermal generators to balance the wind deviation is presented in Section 4.3.

4.3 Problem Formulation

The profit of the VPPO from participating in the day-ahead market when facing uncertainties can be maximized as:

$$\begin{aligned}
&\max_{x} \sum_{t=1}^{N_T} \Bigg[\sum_{g=1}^{N_G} \tilde{\lambda}_t P_{g,t}^{bid} - C_g(P_{g,t}^{RT}) - (SU_{g,t}.(I_{g,t} - I_{g,t-1}))^+ \\
&+ \sum_{d=1}^{N_D} \tilde{\lambda}_t W_{d,t}^{bid} + \tilde{\lambda}_t r_t^o Imb_t^{up} - \tilde{\lambda}_t r_t^u Imb_t^{dn} \\
&+ R_t\big(\tilde{L}_t^{RT} + \rho \sum_{c=1}^{N_C} PD_{c,t}\big) - \tilde{\lambda}_t\big(L_t + \sum_{c=1}^{N_C} POP_{c,t}\big) \Bigg]
\end{aligned} \tag{4.1}$$

where

x $\in \left\{ I_{g,t}, P_{g,t}^{RT}, P_{g,t}^{bid}, W_{d,t}^{bid}, POP_{c,t}, AP_{c,t}^{max}, AP_{c,t}^{min}, PD_{c,t}, \delta_{g,e,t} \right\}$. and $(\tilde{..})$ defines the uncertainty in the input parameter.

The first line of (4.1) defines the profit from thermal generation expressed as the income from the amount bid of power in the day-ahead market minus the cost of production and the thermal generation start-up costs. The second line represents the profit from bidding the wind power into the market and the profit gained from positive imbalances minus the penalties the VPPO might faces as a result of the negative imbalances. The last line defines in its first term the revenue from the loads. Noting that γ which is less than one represents an incentive for the EVs to participate in the coordination, and R is the utility rate which reflects the energy price plus a fixed amount as a revenue for the VPPO. While, the second term is the cost of purchasing the scheduled energy from the market.

The imbalance up term defines the running long status of the producer, where the imbalance down term defines the running short status, at least one of them is zero at any time period t. The producer is running long when the generation is larger than the load or [15]:

$$Imb_t^{up} = \begin{cases} -\Delta P_t \quad \text{if} & \Delta P_t \leq 0 \\ 0 & \text{otherwise} \end{cases} \tag{4.2}$$

$$Imb_t^{dn} = \begin{cases} \Delta P_t \quad \text{if} & \Delta P_t \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{4.3}$$

and,

$$\begin{aligned} \Delta P_t = & \sum_{d=1}^{N_D} W_{d,t}^{bid} - \sum_{d=1}^{N_D} \tilde{W}_{d,t}^{RT} + \sum_{g=1}^{N_G} P_{g,t}^{bid} - \sum_{g=1}^{N_G} P_{g,t}^{RT} \\ & - \sum_{c=1}^{N_C} \big(POP_{c,t} - PD_{c,t}\big) - \big(L_t - \tilde{L}_t^{RT}\big) \end{aligned} \tag{4.4}$$

The producer is running long when the actual generation > the scheduled generation, also he is running long when the scheduled load > the actual load, in this case ΔP_t is negative and equal to the imbalance up. The same concept can be applied to the imbalance down case where ΔP_t is positive. The objective in (4.1) is constrained by:

- Imbalance constraints

$$\Delta P_t = Imb_t^{dn} - Imb_t^{up} \tag{4.5}$$

$$0 \leq Imb_t^{dn} \leq \sum_{g=1}^{N_G} P_g^{max}.I_{g,t} + \sum_{d=1}^{N_D} W_d^{max} - \sum_{c=1}^{N_C} AP_{c,t}^{min} - L_t \tag{4.6}$$

$$0 \leq Imb_t^{up} \leq \sum_{g=1}^{N_G} P_{g,t}^{RT} + \sum_{d=1}^{N_D} \tilde{W}_{d,t}^{RT} - \sum_{c=1}^{N_C} PD_{c,t} - \tilde{L}_t^{RT} \tag{4.7}$$

When the producer is running short or facing imbalance down, the upper bound of the imbalance is the scheduled amounts of generation minus the scheduled load. Its valid to assume safe upper bound by considering the maximum output of the generation. When the producer is running long, the imbalance up is upper bounded by the actual generation minus the actual load.

- Operating limits

$$0 \leq W_{d,t}^{bid} \leq W_d^{max} \tag{4.8}$$

$$I_{g,t}.P_g^{min} \leq P_{g,t}^{RT} \leq P_g^{max}.I_{g,t} \tag{4.9}$$

$$I_{g,t}.P_g^{min} \leq P_{g,t}^{bid} \leq P_g^{max}.I_{g,t} \tag{4.10}$$

- Ramping up/down limits

$$-RD_g \leq P_{g,t}^{RT} - P_{g,t-1}^{RT} \leq RU_g \tag{4.11}$$

- Minimum up/down times

$$\sum_{t=1}^{InitUp_g} (1 - I_{g,t}) = 0 \quad , \tag{4.12}$$

$$\sum_{n=t}^{t+MinUp_g-1} I_{g,n} \geq MinUp_g.(I_{g,t} - I_{g,t-1}) \quad ,$$
$$\forall g, \forall t = InitUp_g + 1....N_T - MinUp_g + 1 \tag{4.13}$$

$$\sum_{n=t}^{N_T} I_{g,n} - (I_{g,t} - I_{g,t-1}) \geq 0 \quad ,$$
$$\forall g, \forall t = N_T - MinUp_g + 2....N_T \tag{4.14}$$

The first constraint of the minimum up times constraints used to define the initial-up time which is the number of the initial periods in which the generator must be on. The second constraint define the the minimum-up time during which is the number of the time periods which the generator must be on before it turns off again. The last constraint applies the minimum-up time constraint for the period of the final $minUp - 1$ times such that, if the generator g is on, it should continue on until the end of the time horizon. Another three equivalent constraints to (4.12) - (4.14) can be included to model the minimum down times.

- Production cost constraints

$$C_g(P_{g,t}^{RT}) = FC_g.\left(I_{g,t}.K_g + \sum_{e=1}^{N_E} Slope_{g,e}.\delta_{g,e,t}\right) \tag{4.15}$$

$$P_{g,t}^{RT} = P_g^{min}.I_{g,t} + \sum_{e=1}^{N_E} \delta_{g,e,t}, \quad \forall g \tag{4.16}$$

$$0 \leq \delta_{g,e,t} \leq BrkPt_{g,e} - BrkPt_{g,e-1} \quad \forall g, e, t \tag{4.17}$$

$$K_g = a_g + b_g P_g^{min} + c_g P_g^{min^2} \tag{4.18}$$

Usually the production cost is defined as quadratic function of the power produced from generator g at time t. To avoid the quadratic function, a piecewise linear approximation is used such that, the exponential curve of the cost is discretized into segments, each segment with a defined slope. Then, the cost is approximated as a function of these segments and slopes a given in Eq. (4.15).

- EV charging power limits

$$0 \leq POP_{c,t} \leq MP_{c,t} \tag{4.19}$$

- EV charge requirement limits

$$\sum_{t=1}^{T\_Dep(1)} PD_{c,t} \geq 0.9MC_c - SOC_{I_c} \tag{4.20a}$$

$$\sum_{t=1}^{T\_Dep(1)} PD_{c,t} \leq MC_c - SOC_{I_c} \tag{4.20b}$$

$$\sum_{t=1}^{T\_Dep(x)_c} PD_{c,t} - (x-1)SOC_c^{reduc} \leq MC_c - SOC_{I_c} \tag{4.20c}$$

$$\sum_{t=1}^{N_T} PD_{c,t} - 4 \times SOC_c^{reduc} \leq MC_c - SOC_{I_c} \tag{4.20d}$$

$$\sum_{t=1}^{N_T} PD_{c,t} - 4 \times SOC_c^{reduc} \geq 0 \tag{4.20e}$$

- EV Additional power limits

$$0 \leq AP_{c,t}^{max} \leq MP_{c,t} \times Av_{c,t} - POP_{c,t}$$
$$\forall c \in N_C, t \in N_T \tag{4.21}$$

$$0 \leq AP_{c,t}^{min} \leq POP_{c,t} \quad \forall c \in N_C, t \in N_T \tag{4.22}$$

- EV Actual power draw limits

$$POP_{c,t} - AP_{c,t}^{min} \leq PD_{c,t} \leq POP_{c,t} + AP_{c,t}^{max}$$
$$\forall c \in N_C, t \in N_T \tag{4.23}$$

4.3.1 Deterministic Model

In the deterministic model the VPPO take his decision with no consideration for the uncertainty such that all the parameters assumed to be accurate. Under the deterministic model the VPPO will not benefit form the imbalance income or incurred any imbalance cost. Hence, the part of the imbalance profit in the objective function will be removed as the constraints (4.2) - (4.7).

4.3.2 Robust Optimization Model

In the robust optimization literature, the uncertainty is handled by defining the uncertain parameters over uncertainty sets which represent all the possible realizations of the uncertain parameter. More details for the uncertainty set are introduced in section (4.3.3).

4.3.3 Uncertainty Set

The selection of the uncertainty set is usually relies into the available information about the uncertain parameter [74]. In this paper, we consider the case of the taking decision process by the VPPO without waiting for the reutilization of the uncertain parameter. In other words, the problem is formulated for the worst-case realization of the uncertainty. Hence, the uncertainty set is defined as $\mathbb{Z} = Z_W \cup Z_\lambda \cup Z_L$ where Z_W is the set of the wind uncertainty and Z_λ ,Z_L is the set of the energy price and the set of the demand respectively. The uncertainty set of the wind power gives the relation between the nominal value of the generation and the lower and upper bounds of the deviation as:

$$Z_W = \left\{ W_t = \hat{W}_t + \gamma_t^+ \overline{W}_t - \gamma_t^- \underline{\mathrm{W}}_t, W_t \geq 0, \gamma_t^+, \gamma_t^- \in \{0,1\}, \forall t \right\} \tag{4.24}$$

where $\hat{W}$ is th nominal value for the wind generation, $\underline{\mathrm{W}}, \overline{W}$ is the lower and upper bounds of the deviation respectively. Clearly, the γ_t^+, γ_t^- at least one of them is equal to zero at each time period t since there is only a positive or a negative deviation at a certain time period t. Similarly, the sets Z_λ for the price and Z_L for the demand are:

$$Z_\lambda = \left\{ \lambda_t = \hat{\lambda}_t + \gamma_t^+ \overline{\lambda}_t - \gamma_t^- \underline{\lambda}_t, \lambda_t \geq 0, \gamma_t^+, \gamma_t^- \in \{0,1\}, \forall t \right\} \tag{4.25}$$

$$Z_L = \left\{ L_t = \hat{L}_t + \gamma_t^+ \overline{L}_t - \gamma_t^- \underline{L}_t, L_t \geq 0, \gamma_t^+, \gamma_t^- \in \{0,1\}, \forall t \right\} \tag{4.26}$$

It worth noting that the uncertainty in the imbalance prices considered as a function of the energy price with the parameters r^o, r^u where $r^u > 1$ and $r^o < 1$. For more about the formulation of this variables, please refer to [46] and [34].

4.3.4 Robust Counterpart

One known method of dealing with uncertainty in the objective function is to reformulate it as a constraint-wise uncertainty [76]. It is known that:

$$\max_{x} \quad \hat{c}^T x \quad ,$$

subject to

$$Ax \leq b \quad \forall x \in X$$

is equivalent to

$$\max_{x,m} \quad m,$$

subject to

$$\hat{c}^T x \geq m \quad \forall c \in C$$

$$Ax \leq b \quad \forall x \in X$$

where C is the uncertainty set for the parameter c, m is an auxiliary variable. Hence, the uncertainty of the objective function was reformulated as a constraint-wise uncertainty. Similarly, the uncertainty in the energy price in model (4.1) and the uncertainty of the other constraints can be reformulated as [55] :

$$
\begin{aligned}
&\max_{x,\Omega} \quad \Omega \\
&S.t. \\
&\sum_{t=1}^{N_T}\Bigg[\sum_{g=1}^{N_G}(\hat{\lambda}_t - \underline{\lambda}_t)P_{g,t}^{bid} - C_g(P_{g,t}^{RT}) - (SU_{g,t}.(I_{g,t} - I_{g,t-1}))^{+} \\
&+ \sum_{d=1}^{N_D}(\hat{\lambda}_t - \underline{\lambda}_t)W_{d,t}^{bid} + (\hat{\lambda}_t - \underline{\lambda}_t)r_t^{o}Imb_t^{up} - (\hat{\lambda}_t + \overline{\lambda}_t)r_t^{u}Imb_t^{dn} \\
&+ R_t\big((\hat{L}_t^{RT} - \underline{L}_t^{RT}) + \rho\sum_{c=1}^{N_C}PD_{c,t}\big) - (\hat{\lambda}_t + \overline{\lambda}_t)\big(L_t + \sum_{c=1}^{N_C}POP_{c,t}\big)\Bigg] \geq \Omega
\end{aligned}
\tag{4.27}
$$

Since its not favorable for robust optimization to deal with equality constraints [76]. Hence the constraint in (4.4) will be replaced by its equivalence :

$$
\begin{aligned}
&Imb_t^{dn} - Imb_t^{up} - \sum_{d=1}^{N_D}W_{d,t}^{bid} - \sum_{g=1}^{N_G}P_{g,t}^{bid} + \sum_{g=1}^{N_G}P_{g,t}^{RT} \\
&+ \sum_{c=1}^{N_C}\big(POP_{c,t} - PD_{c,t}\big) + L_t \leq \left((\hat{L}_t^{RT} - \underline{L}_t^{RT}) - \sum_{d=1}^{N_D}(\hat{W}_t^{RT} + \overline{W}_t^{RT})\right) \times K
\end{aligned}
\tag{4.28}
$$

$$
\begin{aligned}
&Imb_t^{dn} - Imb_t^{up} - \sum_{d=1}^{N_D}W_{d,t}^{bid} - \sum_{g=1}^{N_G}P_{g,t}^{bid} + \sum_{g=1}^{N_G}P_{g,t}^{RT} \\
&+ \sum_{c=1}^{N_C}\big(POP_{c,t} - PD_{c,t}\big) + L_t \geq \left((\hat{L}_t^{RT} + \overline{L}_t^{RT}) - \sum_{d=1}^{N_D}(\hat{W}_t^{RT} - \underline{W}_t^{RT})\right) \times (1 - K)
\end{aligned}
\tag{4.29}
$$

Where K is a binary auxiliary variable to guarantee that only one of (4.28) and (4.29) is active at each time. Furthermore, the constraint (4.7) can be transformed into its robust counterpart as:

$$0 \leq Imb_t^{up} \leq \sum_{g=1}^{N_G} P_{g,t}^{RT} + \sum_{d=1}^{N_D} (\hat{W}_t^{RT} - \underline{W}_t^{RT}) - \sum_{c=1}^{N_C} PD_{c,t} - (\hat{L}_t^{RT} + \overline{L}_t^{RT}) \quad (4.30)$$

Such that we removed all the uncertainties and completed the formulation of the robust counterpart of our model.

4.4 Case Study

A case study for a VPP that serves a small urban area was considered. We aim from this study to assess the benefits of the proposed coordination for both the VPPO and EVs' owners under the considered uncertainties. VPP consists of one wind power plant with installed capacity of 200 MW, five thermal generators with total installed capacity of 340 MW. For detailed characteristics of the wind and the thermal generators, we refer the reader to [15] and [34]. A group of 10000 EVs with 50 similar driving profile representing the Spanish commuting behavior are used. The batteries capacities, EV's characteristics are such that in [15]. A set of 1000 scenario for the wind output, energy price, and the imbalance price, are generated using seasonal autoregressive integrated moving average technique (ARIMA) [34]. Three load profiles (low, nominal,and high) are used. Hence, reducing the scenarios-tree from 1000 to 3 is used by the fast-forward method

[52]. The final size of the scenario-tree is $3^4 = 81$ scenarios. The reduced scenario-tree is used to construct the uncertainty sets for the wind output, energy price, imbalance price, and demand as in Fig. 4.2 to Fig. 4.4.

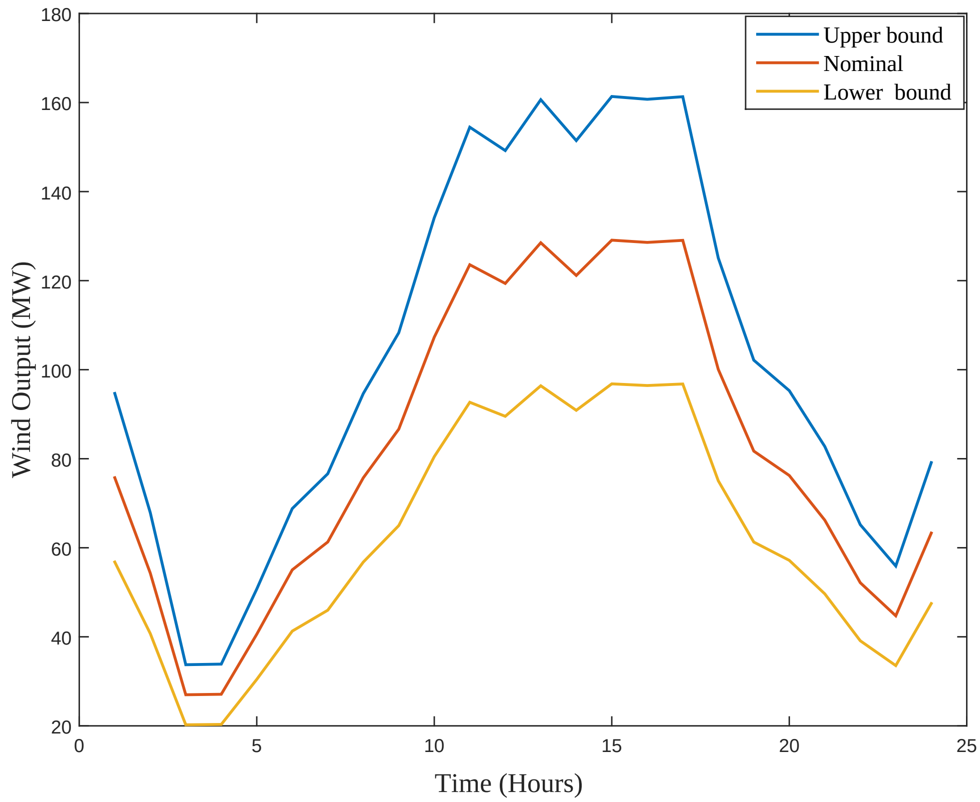

Figure 4.2: Wind nominal values and uncertainty bounds.

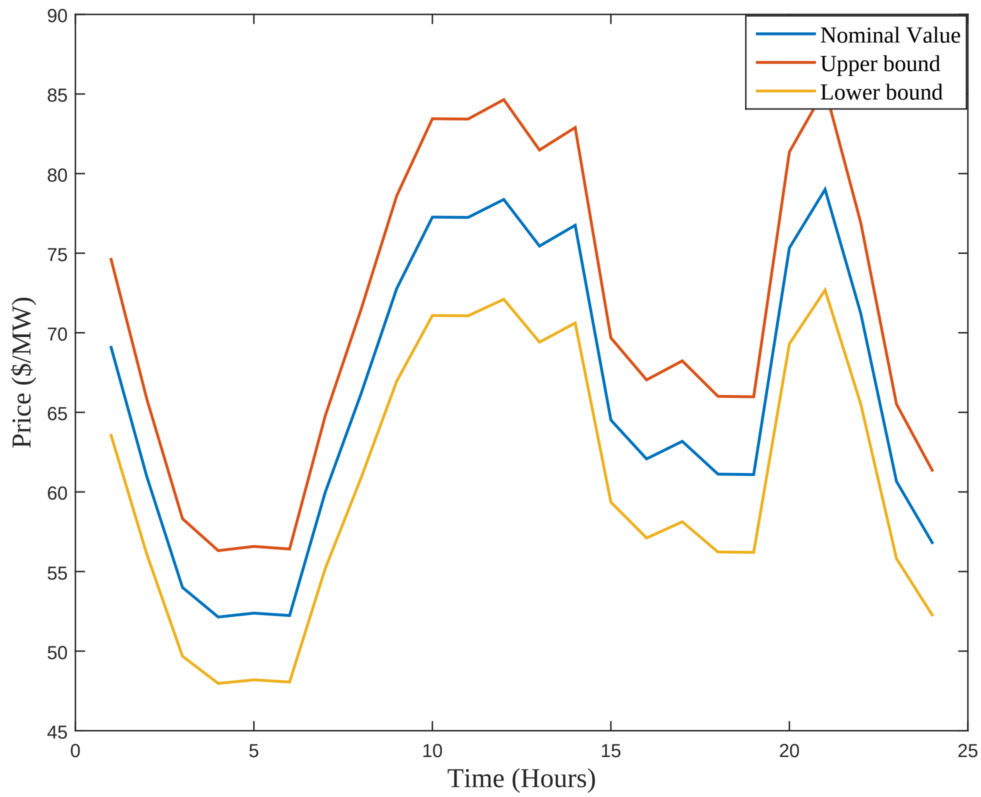

Figure 4.3: Price nominal values and uncertainty bounds.

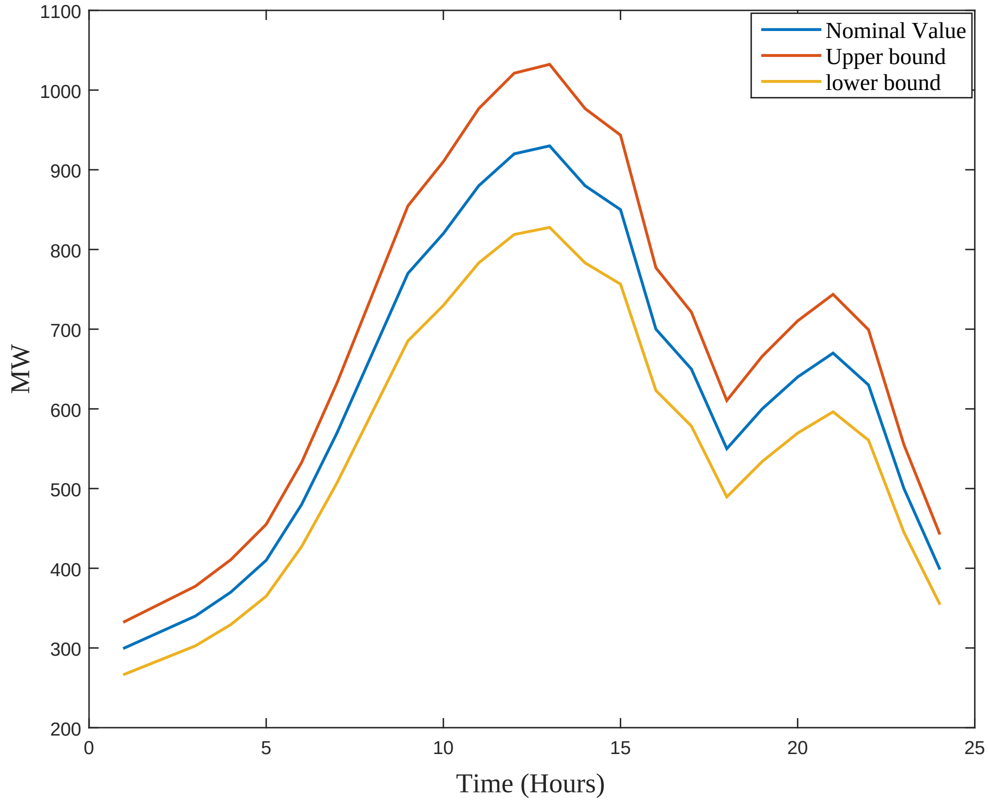

Figure 4.4: Demand nominal values and uncertainty bounds.

The uncertain parameter was considered in the uncertainty set as [nominal value - lower bound, nominal value + upper bound], then the upper and lower bounds modeled as a percentage of the nominal value to represent the uncertainty set as (nominal value $\times(1\pm\theta)$), θ is chosen by the VPPO according to its behavior as a risk-averse or risk-taker decision maker [60]. Clearly, the choice of θ decided the size of the uncertainty set. Three different values for each uncertainty set are considered $\theta_w, \theta_\lambda, \theta_L$ for wind output, energy price, and demand respectively.

For the uncoordinated case, we meant by this that the thermal-wind coordination was considered, but the EVs are not treated as a source of balancing. Furthermore, it is assumed that the the opportunistic charging is used to charge the EVs. In this way the EVs are charged by the maximum charging rate once they are plugged in between 10 A.M and 3 P.M, 6 P.M and 9 P.M. The decision variables of the EVs ($i.e., POP, AP^{max}, ...etc$) are set to zero, and the total amount needed for the EVs charging is added as a constant load.

The solution algorithm was modeled using IBM ILOG CPLEX [77] and executed on a PC with an Intel(R) core ™ i3 @ 2.53 GHz CPU and 6 GB of RAM, the processing time is about 15 seconds.

4.5 Simulation Results

Two cases are considered to assess the effectiveness of the proposed model. In case 1, the robust optimization is used to model the uncertainties of the uncoordinated case between the EVs and wind-thermal generators. In case 2, the coordination between the EVs and the thermal-wind generators was considered under both deterministic and robust models. The profit of the VPPO at the deterministic case was compared with both the coordinated and the uncoordinated profit of the robust model under different levels of uncertainty. Table 4.1 shows the results of the VPPO's profit for the worst case scenario of the realization of the uncertain parameters when the uncertainty set at its extreme bound. However, even the deterministic model outperforms the robust model in terms of profits by $(27972 - 22395)/27972 \simeq 19.4\,\%$, the robust model counts for the worst case realization of the uncertain parameters which keeps the decision maker safe with any realization of the uncertainty. Moreover, moving from the most conservative situation i.e., worst case might increase the profits of the VPPO with considering the uncertainties. The benefits of the coordination is very evident on the profit of the VPPO compared to the uncoordinated case. The coordination gain be given as $(22395 - 21178)/22395 \simeq 5.43\,\%$. The impact of considering the uncertainties using the the robust optimization is very clear when it comes to the non-robust profits. The realized profits was calculated based on the decisions of the aggregator when the nominal values were considered in the scheduling day, while in the actual day the aggregator might face different scenarios of uncertainties. The negative realized profits confirms that considering the deterministic model might misleading the decision maker to the case of unrealized profits. In other words, the uncertainties should be included into the optimization. Moreover, the profits of the aggregator might be increased by considering other cases rather than the worst case.

Model	Profits $
Deterministic Profits	27972
Coordinated Profits	22395
Uncoordinated Profits	21178
Realized Profits with 5%	25251
Realized Profits with 10%	24541
Realized Profits with 15%	24601
Realized W. case Profits	-1496

Table 4.1: VPPO's profits with/without EVs coordination

Unit No.	Time (0-24)
1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
2	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1
3	1 1 1 1 1 1 1 1 1 1 1 0 0 0 1 1 1 1 1 1 1 1 1 1 1
4	0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
5	1 1 1 1 1 0 0 0 0 0 0 1 1 1 1 1 0 0 0 0 0 0 0 0 0

Table 4.2: Thermal units commitment with no coordination

Unit No.	Time (0-24)
1	**0** **0** 1 1 **0** 1 1 1 1 1 **0** 1 **0** 1 **0** 1 **0** **0** 1 1 1 1 1 1
2	1 1 **0** **0** 1 1 1 1 1 1 1 1 1 **0** 1 1 1 1 1 1 1 1 **1** 1
3	1 1 1 1 1 1 1 1 1 1 1 **1** **1** **1** 1 1 1 1 1 1 1 1 1 1
4	0 **1** **1** **1** 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
5	1 1 1 1 1 **0** **0** **0** **0** **0** **0** 1 1 1 1 1 **0** 0 0 0 0 0 0 0

Table 4.3: Thermal units commitment with EVs coordination

Tables 4.2 and 4.3 show the commitment of the thermal generation units in both coordinated and uncoordinated cases. Note that the status which changes was highlighted by bold font.

Fig. 4.5 shows a comparison between the wind power bids in case of EVs coordination and the uncoordinated case. It is clear that the EV coordination helps the

VPPO to bid the wind power more aggressively in the market, which reflects the benefits of the coordination between wind-thermal generators and EVs.

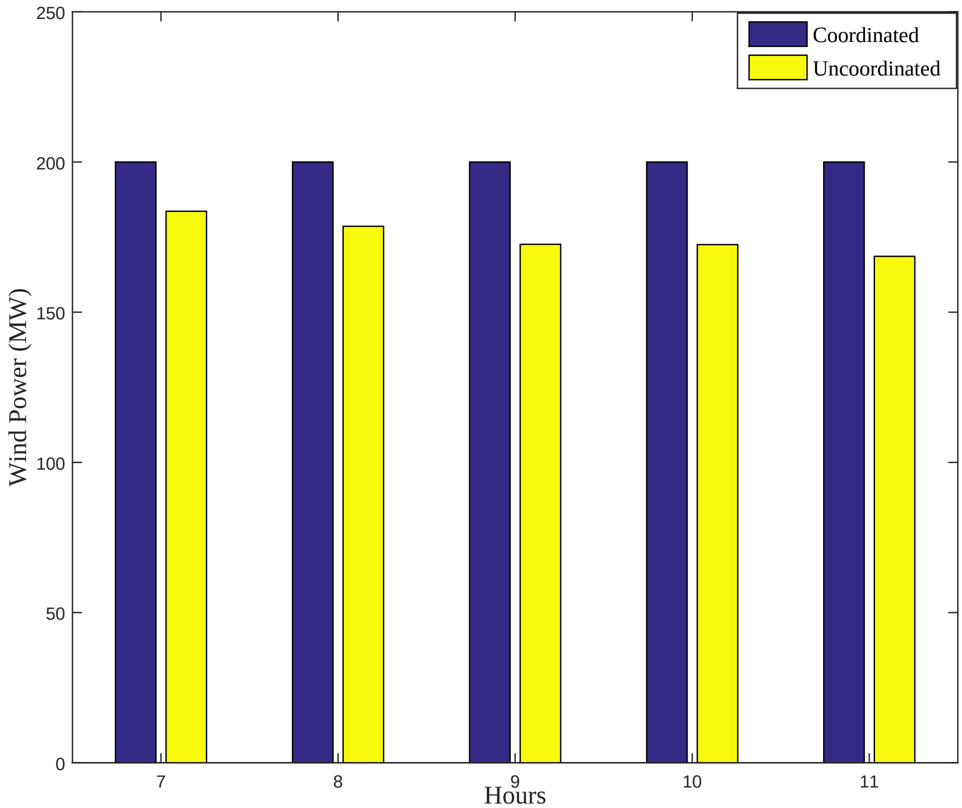

Figure 4.5: Wind power bid offers of selected hours of the simulation day.

4.6 Conclusion

In this chapter, a model of a wind power producer who owns a thermal generation units, and control a number of EVs as a controllable load was proposed. The wind power producer is valid to be considered as an EVs aggregator who submit bids in the day-ahead market. The optimal bidding strategy for the aggregator in the day-ahead market was modeled for the worst case scenario using robust optimization. The uncertainties about the wind output, energy price, imbalance price, and demand was considered. The robust counterpart for the problem was obtained. A case study to assess the validity of the proposed model was established. A comparison between the profit of the wind producer in the case of coordination with EVs and without coordination was conducted. The results show that the profit of the wind power producer will be increased when coordination with the EVs takes a place. Moreover, in case of coordination, the wind producer can bid the wind more aggressively in the day-ahead market.

4.7 List of Publications

- **Ahmed M. Abd El-Moaty**, Wessam Mesbah and Ali T. Al-Awami, Risk-Based Robust Bidding Strategies for EVs' Aggregators in Day-ahead Markets with Uncertainty, To be submitted.

CHAPTER 5

CONCLUSIONS AND FUTURE RESEARCH

In this chapter, the main contributions of this thesis was summarized. Then, a suggestion for some possible future research directions was introduced.

5.1 Summary of Contributions

The main objective of this thesis was to study the impact of the combined integration of wind power and electric vehicles into smart grids. Two projects were conducted to analyze this integration. The conclusion of the thesis can be summarized as follows:

1) The electric vehicles can be considered the most prominent source for mitigating the risks of the wind power intermittent. First, EVs can be used to balance the wind/load system by controlling the charging rate. In this

regard, a game theoretic model for EVs to decide about their actual power draw while maintaining the system balanced was proposed. The balance requirement was aligned with the EVs payoffs by choosing a proper incentive for the EVs to provide the balancing service. A closed form solution for the equilibrium of the game was provided using the KKT optimality conditions, after the proof of the existence and the uniqueness of the equilibrium of the game. Simulation results were carried out to validate the effectiveness of the proposed decentralized model and the closed form solution compared with the centralized solution.

2) The uncertainty of the wind power is one of the main obstacles which faces the power producer when he submit his bidding in the electricity market. The coordination between the wind and the EVs will benefit both the EV owners and the Wind producer. In the fourth chapter of this thesis, a model of a wind power producer was proposed, which is valid to be considered as an EVs aggregator, faced by several uncertainties. The optimal bidding strategy for the aggregator in the day-ahead market was modeled for the worst case scenario using robust optimization. The uncertainties about the wind output, energy price, imbalance price, and demand were considered. The robust counterpart for the problem was obtained. A case study to assess the validity of the proposed model was established and a comparison between the profit of the wind producer in the case of coordination with EVs and without coordination was conducted. The results show that the

profit of the wind power producer will increase when coordination with the EVs takes a place. Moreover, in case of coordination, the wind producer can bid the wind more aggressively in the day-ahead market.

We may conclude this thesis by these findings:

(a) The electric vehicles may be used as a balancing source for the wind-load mismatch effectively.

(b) Proper incentives should be chosen carefully to encourage the EVs owners for participation in V2G services.

(c) The EVs can help the wind power producer to mitigate the risks of the wind output and the energy price, which enables the producer to optimally bid its generation in different electricity markets.

5.2 Future Research

1) Both the wind power, and the electric vehicles have the capability to provide ancillary services to the power grid, such as frequency regulation, and spinning reserve. Participation in these markets could be economically beneficial to wind power producers. Future research can be conducted to analyze the trading behaviors of the wind power producers and models can be built to obtain their optimal bidding strategies in these ancillary service markets.

2) Other models for competition in case of the wind-EVs coordination in the electricity markets may be considered, such as game theory. The impact of

the wind power producer as a price maker in the market may be included. For future work, comparing the advantages and disadvantages of using different models may be studied.

3) Studying other renewable energy sources, such as solar, biomass and hydrothermal which constitute an important part of the future power system structure. The models to obtain the bidding strategies of different types of renewable energy in the electricity market can be built in future research work. The models can be extended for those producers who have multiple types of renewable energy.

APPENDIX

Clearly, the payoff function of the i^{th} EV is a concave function with respect to $PD_{i,t}$ and the set of constraints is a convex set. Hence, the Nash equilibrium of WBG directly follows the work presented in [78, Theorem 2]. Next, we prove the uniqueness of Nash equilibrium. From [78, Theorem 4], the sufficient condition for NE uniqueness in a concave game is that the matrix $G(x) + G^T(x)$ is a negative definite, where $G(x)$ is the Hessian matrix for the payoff functions,

$$G(x) = \begin{bmatrix} \frac{\partial^2 f_1}{\partial^2 x_1} & \frac{\partial^2 f_1}{\partial x_1 \partial x_2} & \cdots & \cdots \\ \frac{\partial^2 f_2}{\partial x_2 \partial x_1} & \frac{\partial^2 f_2}{\partial^2 x_2} & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix} \tag{1}$$

Since the payoff defined in Eq.3.3, the derivatives w.r.t $PD_{i,t}$ can given as:

$$\frac{\partial^2 f_1}{\partial^2 \mathsf{PD_{i,t}}} = -2\beta \qquad \forall i \in N, 1 \leq t \leq T \tag{2}$$

$$\frac{\partial^2 f_1}{\partial \mathsf{PD_{i,t}} \partial \mathsf{PD_{m,t}}} = -\beta \qquad \forall i, m \in N, i \neq m, 1 \leq t \leq T \tag{3}$$

Then

$$G(x) = \begin{bmatrix} -2\beta & -\beta & \dots & -\beta \\ -\beta & -2\beta & \dots & \dots \\ \vdots & \vdots & \vdots & \vdots \\ -\beta & \vdots & \vdots & -2\beta \end{bmatrix} \tag{4}$$

$$= -\beta \begin{bmatrix} 2 & 1 & \dots & 1 \\ 1 & 2 & \dots & \dots \\ \vdots & \vdots & \vdots & \vdots \\ 1 & \vdots & \vdots & 2 \end{bmatrix} \tag{5}$$

For any arbitrary $N \times 1$ non-zero vector r, we have $r^T(G(x) + G^T(x))r$, $G(x)$ is symmetric matrix, also $(G(x) + G^T(x))$ is symmetric, and $G(x) = G^T(x)$

Then,

$$
\begin{aligned}
r^T(G(x)+G^T(x))r &= -2\beta r^T G(x) r \\
&= -2\beta \quad \text{(sum of squares)} \\
&< 0.
\end{aligned}
\tag{6}
$$

Then, $r^T(G(x)+G^T(x))r$ is negative definite, which implies that the NE is unique [78, Theorem 4]. NE is given numerically using [78, Theorem 10].

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